INTERACTIONS BETWEEN MUTUAL FUND FLOWS, ASSET PERFORMANCES AND INVESTOR BEHAVIOURS IN UNITED STATES

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By

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ABSTRACT

Mutual fund is a burgeoning business in not only US but the world. There is a growing tendency that participations of individual investors in financial market are migrated to mutual funds, an indirect channel to invest. Thus, the flows to and out of mutual funds, once a neglected topic, are becoming a new field for financial study.

The primary instrument and subject of my PhD is mutual fund flows. Mutual fund flows have special merits for academic research. Firstly, it is purely driven by demands but not supplies, as the supply elasticity of mutual fund is nearly infinite. The characteristic reveals investor behaviours and decisions in a mass scale. Traditional instruments for behaviour studies relies on asset prices and volumes, which are less exogeneous as they are driven by both demand and supply. Secondly, mutual funds specify their objectives and asset classes in prospectus. The characteristics help us understand how investors respond to changing market conditions by changing their exposures on asset classes or styles. Thirdly, a majority of individual investors in mutual funds (as suggested by ICI statistics) provides a natural field for behavioural finance. Fortunately, data is available not only at aggregated level, but also individual and account level, which serve as a great supplement to the existing studies using trading data.

The second chapter is based on a simple hypothesis: if flows are (rationally) responding to fund performance, what information does the flow-performance sensitivity convey? How flow, a measure of actual fund investor trading decisions, helps us decompose and finely measure the outcome of these investors? The study is based on several established papers on flow-performance relationships in mutual fund market. Warther (1995) is a pioneer paper that discovers a significant correlation between flows and performance. Sirri and Tufano (1998) discovers a convex-shaped flow-performance function and attributes the cause to asymmetrical information. Berk and Green (2004) established a model in which investors trade against good performers and against bad performers but funds themselves suffer from diseconomy of scale. As the fund change in size, it deviates from optimal portfolio size and

result to better or worse performance. Huang, Wei and Yan (2012) argues that flow-performance sensitivity is a rational investor learning process. Based on their arguments, I obtain a simple but effective proxy for investor sophistication: the sensitivity of flows to recent (abnormal) performances. To granularly measure their respective performance, I decompose their performance into three aspects: abnormal returns, fees and timings, a scheme proposed in Fama (1972). The abnormal return is alpha on a four-factor model, which is a traditional before fee, relative measure of whether a fund has beat the market. Fee selection takes into account the average fees that jeopardize the performance and timing cost is measured by "performance gap", a concept used in Nesbitt (1995); Dichev (2007); Friesen and Sapp (2007); Bullard, Friesen and Sapp (2008). The result is that sophisticated investors earn higher risk adjusted returns and avoid high fees. In addition, investors' timing performance can be greatly improved by trading less, with the most significant improvements seen on most sophisticated investors.

The research question in third chapter is: is there a calendar effect for flow-performance relationship? Does the shape of the function change across the months and what drives the change? The study fills the gap by emphasizing several exogeneous factor of flow-return relationship such as portfolio rebalance and tax-loss selling which interact with calendar dates. Previous literature commonly finds a convex function. Chevalier and Ellison (1997) is first to document the convexity and they argue the convexity may incentivize agency problems. Sirri and Tufano (1998) explained using information search cost and Lynch and Musto (2003) explained with survivalship bias of mutual fund strategies. However, all the study examines only average shape of the flow-performance function. None of them attempt to tackle calendar effect. Calendar effect is potentially a strong determinant of flow-performance relationship. Factors such as tax-loss selling (Constantinides (1983)), portfolio rebalance, disposition effect (Kaustia 2011)) and seasonal variation in risk appetite (Kamstra *et al.* 2017) may interact with dates and change the flow-performance relationship. In this study, I conduct a similar flow-performance regression for each month. The regression is piecewise which separates the sensitivity of mutual fund flows to returns into five parts. I also construct a concise measure of whether a group of funds are bought or sold at any time during the year to disentangle several confounding effects. I find that the shape of the function does change throughout the year and they are affected by tax-loss selling and portfolio rebalance.

In fourth chapter, I focus on a special group of funds, the leveraged funds, which mainly caters for day traders. *The research question is whether their flows reflect market wide sentiment.* Leveraged funds are funds that allows investors to bet on daily performance of stock indexes with leverage and direction. As these funds track only daily index returns and investment horizon longer than one day will result to material deviation from index returns, these funds are unlikely used by mid- or long-term optimizers. As common study suggest too much trading can be harmful (Barber and Odean 2000), I notice that the flows for these funds may be sentiment driven. In this study, I obtain daily flows of nearly 100 largest leveraged funds trading in US and extract the first principal component from these funds. In addition, I follow Baker and Wurgler (2006a) to construct a daily sentiment index (the alternative sentiment measure) from several market variables, which are purposely chosen to be unrelated to fund markets. I find that the first component from leveraged funds is associated with investors' migration between bull and bear funds and it has strong correlation with our alternative daily sentiment measure. In a later test, the two sentiment measures have similar price impact as a hypothetical sentiment measure would have. I have also examined the limits of arbitrage effect proposed in Shleifer and Vishny (1997). The sentiment component predicts similar cross-section of price revision for up to 7 days into future.

AUTHOR'S DECLARATION

I declare that, except where explicit reference is made to the contribution of others, that this dissertation is the result of my own work and has not been submitted for any other degree at the University of Glasgow or any other institution.

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CHAPTER 1

LITERATURE REVIEW

Chapter 1 - Literature Review

1.1 The US Mutual Fund Market and Its Investors

The US mutual fund market is not only a burgeoning business, but also the world's largest. Starting from the first mutual fund, Massachusetts Investors Trust, value of total investable securities held by all US mutual funds and ETFs (mutual funds in this study refer to mutual funds and ETFs hereafter) have grown up to nearly 18 billion Dollars as of 2015, a considerable amount. Mutual funds, naturally, becomes the largest investor in US financial market. It also holds nearly half of world mutual fund assets (47%), making it an outstandingly representative sample to conduct research.

US mutual funds are extremely influential to the financial market they invest in, given the huge share of securities they hold. As of 2015, mutual funds hold 31 percent of outstanding equities, 40 percent of commercial paper, 26 percent of municipal bond, 19 percent of government bond and 11 percent treasury securities. In addition, mutual funds' annual turnover of these securities is found to be significant. The emerging presence of mutual fund transactions has spurred much academic interests.

Initial studies focus on the role of mutual funds as major financial institutions. The sheer amount of asset held by mutual funds means their transactions may stir anomalous market movements, deviate asset price forms the fundamental level suggested by traditional financial theory. The managers, given the discretion of these assets, are also under limelight. The exposure comes from that they act as the discoverer of "free launch" (though not so for index funds), aiming to select a combination of financial assets to achieve desired level of performance in terms of the risk born. Another aspect is that mutual funds are compensated by millions of investors. They act as an agent for these investors to maximize their collective utility, so that these compensations are justified. These studies focus on whether mutual funds drive the market to the right track or not, or whether customers are paying for a reasonable service.

However, some of the scholars takes the perspective of investors, rather than mutual fund as an entity. The practice comes from the dominant participation of individuals in mutual fund industry. As of 2015, mutual funds manage 22 percent of all household financial assets. These means household investors entrust a significant amount of financial assets to professional wealth managers. Meanwhile, the major customer of US mutual funds is retail investors. A staggering 89% of all mutual fund assets are held by retail investors. Given these facts, it is reasonable to think the behaviour of mutual fund are at largely driven by the collective decision of the pool of investors, rather than the discretionary decision of asset managers, which could have been no less rational if made all by their own. In other world, this perception of mutual funds view managers as a passive agent who are exposed to demand shocks from investors, impaired of the ability to make his very own decision. When investors channel funds into or withdraw funds from the asset pool, the managers have to choose to expand or shrink their extant positions.

Traditional financial theory suggests a frictionless market in terms of informational efficiency or risk-return trade off. It is also assumed that every economic agent act as a perfect representative investor so that everyone selects the same combination of risky assets and a desired proportion of riskless assets, as known as The Two Funds Theorem. There will be no room for active investments under this setting. The actuality of mutual fund industry, coupled with the asset allocation puzzle documented by, make the mere existence of active mutual funds puzzling enough. Questions on why so many individual investors delegate investments to asset managers and why active investment approach continue to survive has been raised many times. In addition, academics try to examine if the presence of these investors has been destabilizing the market.

The answer may lie in investor behaviours, given the plethora of evidences on the irrationality of individual investors, such as herding, overconfidence, loss aversion and gambling. These behavioural biases are accused to have caused many documented financial anomalies. What’s troubling is that these assumed irrational individuals are behind billions of cash flows channeled in and out of mutual fund market every year. The view that the behaviours of mutual funds unavoidably inherit that of their investor's demand a thorough understanding of investor's constitution, sophistication, risk and pricing preference, behavioural biases and performance. With a deeper understanding of these patterns, three major benefits are expected: The regulatory bodies will obtain more guidance on future improvements on regulations; The fund management companies will gain more information on their customers and optimize their product line; The investors will learn from the past and learn the right way to invest.

Moreover, the linkage of investor, pooled portfolios and the financial market makes mutual funds an exceptional field to conduct research on investor behaviour. The major instrument used in mutual fund study is mutual fund flow. The mutual fund flow is the net increase in mutual fund assets due to the purchase and redemption of mutual fund investors. It reflects the demand shock from investors since any capital gain/losses are already deflated. Fund flows can easily be calculated by the AUM and NAV provided by fund companies. Various institutions also report aggregate mutual fund flows to monitor incremental transactions in the industry. For example, Investment Company Institute report aggregated weekly mutual fund flows for equity, bond, money market, mixed assets and other funds. According to ICI, US mutual funds have seen inflow of 104 billion Dollars in 2014 and an outflow of 105 billion Dollars in 2015. Both the stock and the increments of money is gargantuan enough to move the market. Some institutions like Trimtabs and ETFGlobal also report mutual fund flows at daily level. The availability of daily fund flows spawn various studies on price pressure (Ben-Rephael, Kandel and Wohl 2011) or investors sentiment (Goetzmann, Massa and Rouwenhorst 2000; Ben-Rephael, Kandel and Wohl 2012).

Give the wide availability of price and trading volume data on many asset classes, one may question the point to spend any effort on fund flows. However, flows feature many unique advantages otherwise unavailable on traditional datum. One advantage is that fund flows are signed, reflecting not only the magnitude, but also the direction of the trade. Since it is a general practice of mutual fund companies to report Asset Under Management and Net Asset Value at a dedicated frequency, signed flows are available in fund level. Had it been stock data, information on the direction of the trade could only have been computed from high frequency data, a category which is not easily available. Another advantage is that mutual fund flows almost reflect the pure demand shock from its investors. The contractual arrangement of mutual funds ensures that its investors (the demand side) can redeem or purchase shares from mutual fund companies (the supply side) at the reported NAV at any time, unless the mutual fund companies' default, which is a highly unlikely scenario. In upward market, fund managers are likely to experience fund inflows, resulting to a passive expansion in AUM. In downward market, managers suffer from redemptions, resulting to a passive shrinkage in AUM. Although in some cases fund companies adopt measures like redemption charges to decelerate these disruptions, they can hardly prevent them.

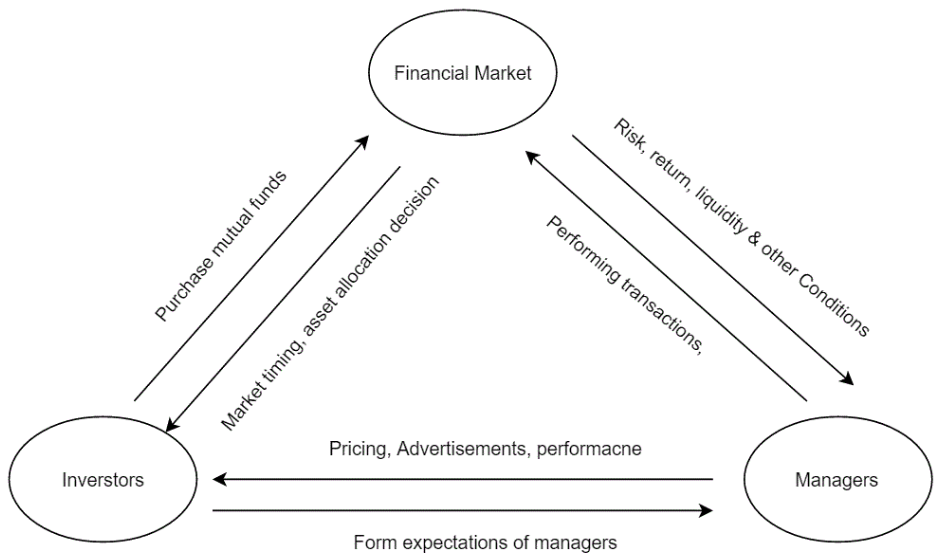


Figure 1-1 The Relationship Between Mutual Fund Investors, Managers and The Financial Market

Investors also migrate between funds. Fund market provide a channel for them to move to the asset class with desired risk-return profile. The direction depends on the expected risk premia on the asset class. Besides purchase and redemption directly from other funds, to facilitate these migrations, many fund companies provide low cost service for investors to transfer position within its own fund family (Fant 1999). Therefore, fund flows are a valuable ground to monitor the asset allocation decision of investors. Although detailed measure of inter-asset fund flows is not possibly available (since fund market is anonymous), useable measure of these migrations has already been invented (Chalmers, Kaul and Phillips 2013). Apart from traditional instruments, the inter-assets flows helps answer problems like equity risk premium (Goetzmann, Massa and Rouwenhorst (2000), investor heterogeneity (Jank 2012) or the existence of noise traders (Indro 2004; Ben-Rephael, Kandel and Wohl 2012).

Therefore, the positioning of this thesis is a study on behaviours of mutual fund investors, with the help of mutual fund flows. Since investors, fund manager and the financial market are closely related, any combination of the three spur interactions, and these are all potential ground for research. These interactions are initiated by mutual fund investors, based on their judgement of the market prospect or fund quality, executed by mutual fund managers and absorbed by the market. A study on mutual funds must reside in any of these combinations and the discovered causal relationships bear various implications. It is illustrated in Figure 1-1. For example, a traditional field of mutual fund study is to examine the relationship between managers and the market, since the managers are the one who directly interact with the market. Out of this concern, some ask whether fund managers time the market well (Treynor and Mazuy 1966; Andonov, Bauer and Cremers 2012) and whether their collective transactions cause distortions in asset prices (Lakonishok et al. 1992; Coval and Stafford 2007). The common instruments are portfolio holding data. A typical question on the relationships between investors and the managers is whether mutual funds are well priced (Sharpe 1991; Christoffersen and Musto 2002) and if investors are rational in reacting to these pricing schemes (Gruber 1996; Barber, Odean and Zheng 2005). Besides, whether investors are successful in picking good managers are also well studied, although results are mixed (Gruber 1996; Carhart 1997; Zheng 1999; Sapp and Tiwari 2004). Similar to my study, this class of studies often use fund flows as a proxy of investors' actions.

Figure 1-1 is a handy framework to initiate any mutual fund studies, and all three chapters in this thesis will be organized by this framework. Unfortunately, due to the space limitations and given the ample literature on mutual fund itself and its managers, I only cover the behaviour of mutual funds' investors. That is to say, topic on the relationship between fund managers and the market such as "fire sale", price pressure, "stale price" (Nanda, Wang and Zheng 2009) and "closet indexing" (Gil-Bazo and Ruiz-Verdú 2009) will not be covered.

1.2 Classic Topics in Mutual Fund Studies

As illustrated in the last section, topics in mutual fund studies span a very broad range, for example market efficiency, information asymmetry, consumer behaviour or behavioural finance. Although some of the topic is not directly related to this thesis, these studies are often milestones which help establish basic perception on the mutual fund industry. Some of the methodologies used in these papers became the de facto standard for later mutual fund studies, or even the broader field of asset pricing, like Carhart (1997)'s Four Factor pricing model. Before proceeding to detailed research topic, I feel the urge to introduce readers into some important topic in mutual fund studies.

1.2.1 Persistence in Mutual Fund Performance

The quest into the patterns of mutual fund performance has a long standing in past literature. One of the most puzzling fact is that mutual fund performance is persistent – past winner funds tends to be the future winners, given some pre-defined time interval; past losers tends to be future winners. There are as many definition of performance persistence as definitions of performance, since there is no catch-all consensus on which should be the ultimate measure for performance. The persistence can be found in performance measured in almost all ways, including risk adjusted return, gross return, rank and net alpha. The phenomenon is puzzling since the weak form Efficient Market Hypothesis by Fama (1970) argues that there is no profitable strategies by extrapolating past asset prices, since past prices have already absorbed all available information. The theory also implies that price is not forecastable. However, the persistence in mutual fund return defy this logic. The persistence suggest that return chasing, at least within time horizon when persistence exist, can be rational, an investment strategy traditional efficient market supporters has long been refuting. Another information performance persistence convey is the potential existence of managerial quality. If managerial quality is an underlying factor of actively managed portfolios and assume that manager quality persists, return has reason to persist since good managers is more competitive with regards to bad managers. Good managers thus earn higher abnormal return at the expense of bad managers. What makes the issue perplexing is the discovery of return persistence of passive portfolios Jegadeesh and Titman (1993), as known as the momentum effect or "Hot Hand Effect". This type of persistence is not attributable to manager quality; thus behavioural explanations emerge. As we can see, return persistence are subjected to interpretations. It can spawn many interesting topics, not only restricted to mutual fund studies but also general asset pricing studies.

Initial attempt on fund return persistence starts from Grinblatt & Titman (1992). They aim to find if there is persistence in risk adjusted mutual fund performance. They adjusted mutual fund return using a set of 6 risk factors which is similar to Fama & French (1992)'s Three Factor Model, since it was a time when the model was not widely recognized. The risk factors include size, dividend yield, co-skewness with the monthly rebalanced equally weighted index, interest rate sensitivity, past returns over the previous three years, and beta. The abnormal returns for each of 273 mutual funds are thus calculated from time series regressions within first half of sample period. When the cross-section of abnormal returns is computed, they are used to predict the cross-section of abnormal returns in the second half of the sample. They also corrected for cross-sectional correlations. This is a methodology similar to the one used in Fama & MacBeth (1973). The result shows that risk adjusted mutual fund returns can be used to predict future risk adjusted returns. The study of Grinblatt & Titman (1992) is constrained in frequency, due to the relative short sample period. The tested persistence is only in 5 years horizon.

Hendricks et al. (1993) offer more powerful test by using alternative frequencies. They specifically look into relative performance measure, the performance rank for the cross-section of funds in some dedicated period. They argue that since performance ranks are often published in canonical sources and widely followed, it is more salient to investors than other measures of performance. Performance rank could be gross, net of fee or risk adjusted. The only difference is that they are in ordinal terms. Hendricks et al. (1993) adjust quarterly net-of fee return of 165 mutual funds using a broad stock market return; a set of factors used by Grinblatt & Titman (1992) and a mutual fund market return. They adopted a methodology of testing predictabilities in residual returns. Statistical evidence points to persistence in relative performance. In addition, they make further test on the economic attainability of persistence. In an evaluation period, they rank funds with risk adjusted return and sort all funds into 8 octiles. A long-short strategy longing top portfolio and shorting bottom portfolios yield significant short term (optimally at 4 quarters) risk adjusted return. The result is stronger by using fund market index albeit weak using other risk factors. Hendricks et al. (1993)'s result not only illustrate the existence of return persistence, but also explore possibility of trading strategy and the horizon to this persistence. However, although their study is titled "hot hands in mutual funds", they do not specifically claim if the hot hand phenomenon is due to behavioural, manager quality or underlying risk factors.

Grinblatt et al. (1995) examine the transaction of mutual fund managers. They found that a large proportion of mutual funds are "momentum" investors: they tend to buy funds with superior recent returns. What's more intriguing is that these fund performed better than peer funds. Although their aim is not on return persistence, their result shed light on a potential reason why persistence exists: some mutual funds are portfolios which have some exposure on the momentum factor in security market. The momentum in securities pass on to the mutual fund. Whether fund managers actively seek exposure on momentum or they have stumbled upon momentum is still unknown.

Elton et al. (1996) develops from Hendricks et al. (1993). They differ since they use the Three Factor Model to adjust fund returns. In addition, they examine if performance measured in gross return and rankings is also persistent. The methodologies they use is also similar to Hendricks et al. (1993), which is to explore causal relationship between past performance measure and future performance measure cross-sectionally. Since they select different performance measure, they provide additional test if past risk adjusted return predict future performance measure. The result is that past risk adjusted return not only predict future risk adjusted return, but also future gross return, especially for extreme return deciles. They also find that the extreme returns and idiosyncratic risks are associated with extreme fees, and fees seems to be negatively related to these extreme returns. When funds with extreme fees and noisy returns are eliminated, the extremeness of top and bottom deciles are reduced to a large extent (about a half). Another finding is that although 1 year return and 3 year returns are both predictive of future performance, it seems the predictive power of 1 year returns are more powerful. These relationships suggest that persistence is not only a relatively short term phenomenon, but also applicable to various performance measures. Another contribution of Elton et al. (1996) is they proved that chasing the winner, or weighting up best recent performers is somewhat economically optimal. They construct fund portfolios with more weight on recent winners and the Sharpe Ratio of the portfolio is higher than passive portfolios. This evidence suggests that there is some unique factor to active investment compared to passive portfolios. Recognizing and extrapolating the factor is economically rational since individuals gain utility from it.

The later literature is largely focused on which this factor represents. As illustrated earlier in this section, the factors beg various explanations. It could be the manager ability, a risk exposure or a behavioural factor. Gruber (1996) believes that the factor represents manager ability. The basic logic is that any mutual fund investors can purchase and redeem the funds at the reported NAV at any time. Whether a fund has good or bad manager, the only cost in carrying the fund is to pay the fees specified by the fund company. If these fees are not commensurate with managerial ability, the fund return will be predictable, since holding a good and a bad fund with same fees is not economically equivalent in this scenario.

Gruber (1996) dedicated a whole section for persistence. The difference of Gruber (1996) is that he uses various measure of performance, including alpha, gross return and expense ratio to forecast alpha. The alpha is also a different version by adding a bond factor in Three Factor Model. This is exactly the reverse to Elton et al. (1996). He finds that while the three measure all forecast alpha, the alpha itself makes the best forecast. He also confirms the finding of Elton et al. (1996) that expenses are somewhat negatively related to future performance. Gruber (1996) tries to explain the phenomenon by emphasizing the existence of manager quality. If the argument is correct, it obvious that good managers charge less while bad managers charge more.

Carhart (1997) refutes the argument that manager quality is the underlying factor of return persistence. He attributes return persistence to stock momentum, a widely documented financial anomaly. That is to say, the observed manager quality is an artifact of stock momentum. Past performance predicts future performance not because the managers continue they streak, but because past performance are related to momentum factor. The biggest contribution of Carhart (1997) is to construct a yearly "winner minus loser" portfolio, on which the return is regarded as the mimicking return for monthly momentum factor. The factor is then used in risk adjustment. Carhart (1996) rebuilt the causality test on Elton et al. (1996) and Gruber (1996) by the new alpha measure. He finds that the momentum factor explains away a significant amount of short term predictive relationship found in these studies. This is a strong evidence against the existence of manager ability. Carhart (1997) also examine 3-year horizon. He finds that only the top and bottom performance deciles tends to survive the risk adjustments including momentum factor. More intriguing is that funds in bottom performance deciles are more likely to do bad than funds in top decile doing good. The author yields a conclusion that manager quality barely exists; value and momentum along with fees and transaction costs are attributable to the return persistence.

Harless & Peterson (1998) notice that the long-term persistence of loser funds coexists with the short-term persistence of winner funds. They argue that while past literature assume that investors rationally respond to past risk-adjusted returns, it is possible that they are chasing return blindly, since individuals are documented to be affected by heuristic bias. Harless & Peterson (1998) highlight that investors may respond to gross, unadjusted return instead of adjusted return. In addition, representative bias drive them to weight recent extreme return instead of risk adjusted return. It is one of the first paper to adopt a behavioural explanation.

Bollen & Busse (2005) believes that the persistence of mutual fund return is a short-lived phenomenon. Their contribution is to examine the short-term performance persistence since they use daily data instead of the monthly or yearly data found in previous literature. For example, Carhart (1997) rank funds by their returns in past 1 to 3 years. Another contribution is the various robust test used in this study. Firstly, in one of the risk adjustment measures, they use a measure of market timing ability of managers, an extension over previous risk-based benchmarks. Secondly, they sort not only on past abnormal returns, but also on past gross returns. When sorted on past returns, the post-ranking return difference disappear. Thirdly, the higher frequency of data grants them extra flexibility as to be able to use the conditional model proposed by Edelen (1999). While they have found short term persistence in return, they argue that investors are hardly able to exploit them, since the cost of doing so offset the benefits.

Kosowski et al. (2006) relates the short-term persistence of abnormal return to managerial abilities of "a sizable minority of managers". However, they are cautious because this persistence may only indicate the luck of this group of managers instead of genuine ability. Out of this concern, they adopt several bootstrap methods on the funds with persistent positive alphas. The theory behind these bootstrap methods is to compare observed successful rate of managers to what have been indicated by probability. Their results are largely similar to previous literature: there are strong evidence that there are very good ("star") managers in the top performing deciles, and their streak is not due to luck. In the bottom deciles, bad managers also persist. However, their reason for low rank is largely due to costs. When funds are ranked both pre-cost and net-of-cost, the low rank funds stay in the bottom deciles only for the second scenario. The study of Kosowski et al. (2006) has two important implications. Firstly, they conclude that performance persistence is a short-lived phenomenon. The annual window used in many studies, for example Carhart (1997) are not capable to capture this persistence. Secondly, they briefly discussed why performance may not persist longer. They argue that the decreasing return to scale and fees erode long term abnormal returns.

Fama & French (2010) takes an efficient market view. They argue that whether performance is measured net-of-fee or gross-of-fee matters for persistence study, since an informationally efficient market should grant mutual funds an alpha which is equal to the fees received by managers. In addition, they also warn that traditional methodology of detecting managerial ability through persistence suffer from the caveat discussed in Berk & Green (2004). The competitive nature of mutual funds may erode any abnormal returns since fund investors will flock to good performers and create diseconomy of scale. The persistence found in mutual funds studies may be luck rather than manager ability. To identify managerial skill, Fama and French (2010) use a bootstrap test which is similar to Kosowski et al. (2006). They compare the empirical distribution of alpha to a hypothetical distribution where all mutual funds have a true alpha of zero (the idea comes from the concept "equilibrium accounting"). The result shows that few funds can break up for the fees. Even the top decile funds can barely provide alpha higher than fees. This is an evidence against the result of Kosowski et al. (2006) where the authors claim the existence of star managers. Their result consolidates the findings of Carhart (1997) by attributing the persistence of mutual fund return to factors outside manager skills.

Lou (2012) approached the persistence question from the perspective of the price pressure. He argues that the hot hands of mutual funds are resulted from the linkage of mutual fund flows to mutual fund returns. If mutual fund investors allocate excessively to recent best performers, these funds will be forced to purchase more of its recent holdings. When fund flows are large, it creates persistence in security returns, which are reflected in the fund NAVs. When price deviate from fundamental because of the price pressure, it will be reverted in the long run.

As we can see, the persistence of mutual fund return is involved in a complex web of interactions among fund managers, investors and market. In addition, the non-experimental nature of financial data obscures any statistical test aimed at exploring the reason behind the persistence. Although sophisticated mathematical instruments has been used for this topic like Kosowski et al. (2006) and Fama and French (2010), the results is still highly subjected to interpretations. However, a clear tendency of current literature is to focus on behavioural explanations instead of rational explanations. This class of literature reject the existence of continuing success of any managers under the assumption of competitive, efficient market while attributing the persistence to behavioural bias of investors and other factors such as fees. As the statistical technique advance and potential emergence of quality, alternative datasets (for example experimental or questionnaires), I am hoping to see more breakthroughs on this issue in further studies.

1.2.2 The Relationship Between Flows and Returns

1.2.2.1 Average Flow-Performance Relationship

Apart from return persistence, academics have discovered more abnormalities in mutual fund market, one of which being the relationship between flows and returns. Moreover, it is also an important branch of study on customers' response to fund characteristics, since tracking record itself also shapes a fund. Mounting evidence have indicated that the flows in and out of mutual funds are related to fund and capital market returns. If contemporary relationships are fully justified by the simultaneous diffusion of information into asset prices, many studies have found a relationship between flows and lagged returns. This is abnormal because the efficient market hypothesis suggest that past asset price reflect any available information in the past thus is not indicative of future performance of the asset. Acting upon past returns for future purchase and redemptions seems irrational in this sense (Patel, Zeckhauser and Hendricks 1994). If investors allocate based on the recent performance of asset classes and assume that assets prices are efficient, they are likely to lose money in the long run due to transaction cost. However, the issue is as complex as return persistence so straight conclusion cannot be achieved. Mutual fund as actively managed portfolios are not solely dependent on the decisions of mutual fund investors. The existence of managers is a potential factor in determining fund returns compared to the passive portfolios studied in asset pricing literature. Whether investors are extrapolating price pattern or managerial abilities hidden in those prices are unclear. Even if managerial abilities do not exist, recent development on asset pricing suggest that expected returns on assets are time-varying, for example Ferson (1989); Bodurtha & Mark (1991); Lettau & Ludvigson (2001); Chordia & Shivakumar (2002). In addition, investors are found to be heterogeneous. The assumption of a representative investor in traditional finance failed to capture the difference in risk appetite and expectations. When investors are heterogeneous and expected returns are time-varying, fund flows are inclusive of these factors.

Ippolito (1992) is one of the first major papers to document the relationship between flows and return. The author takes a stance that flows react to returns because investors need time to detect managerial ability hidden in fund returns. The mutual funds provide relatively homogeneous services however they differ in quality. The realization of mutual fund returns reveals the product quality thus the interaction of flows and returns is a bounding process. When investors vote by foot, that is to flock to good funds and flee from bad funds, they are helping fund market to achieve a positive equilibrium (what he call consumer vigilance). Ippolito suggest that the quality signals are in return residual, the return after risk adjustments. The author regresses the percentage fund flows on lagged performance residual and found a positive significant relationship up to three lags. The author's view of past return for actively managed portfolio is that it reflects long term quality of the fund which is ready to be exploited, instead of noise which is what efficient market theory suggested. Another important implication is that moving towards recent good performers and away from recent bad performers is a rational consumer behaviour which provide an elimination mechanism in fund market.

While Ippolito (1994) examine the cross-sectional relationship of fund flow and fund performance, Warther (1995) looks at aggregate mutual fund flow and aggregate market return. Although market return may differ from fund-level return since 1. Market return is passive portfolio and 2. When returns are aggregated many cross-sectional information on funds is canceled out, the efficient market argument at the start of the section is still valid. The biggest contribution of Warther (1995) is it established a framework on the causal relationship between flow and return which is adopted by many later studies.

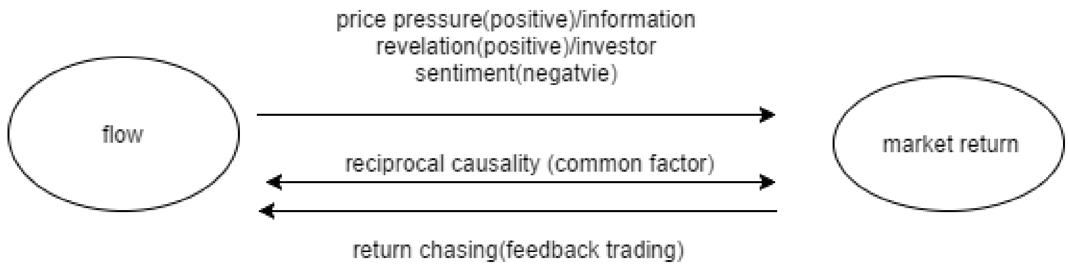


Figure 1-2 The Causal Relationship Between Flow and Return in Warther (1995)

Figure 1-2 Illustrate the hypothesis listed by Warther (1995) on the causal relationships between return and flows. The author discusses scenarios under which the causality takes different directions and signs. The first is “Feedback Trader Hypothesis” which states that investors may act upon past market return so that lagged returns predict flows. The price pressure story states that lagged flows predict return since flows temporarily increase demand on certain asset class so that future return follow the path and then reverse to fundamental. Information revelation assume that fund investors are collectively smart so that flows reveal valid information on future prospect of the market, sot that lagged flows are positively related to returns. The investor sentiment argument assume that investors are not collectively smart so that past flows drive asset prices from fundamentals. As a result, future asset prices move in opposite direction to past flows. In addition, if reciprocal causality or contemporaneous relationship is found, the implication is harder to digest. It may be due to common factors affecting both, or very quick exchange of causality between both.

This graph easily accommodates virtually every study on this topic since every scenario are included. I will use this framework for the reviews that ensue. For example, the result of Ippolito (1994) that flows lagged fund returns implies past returns convey valid information about prospect of the fund which is revealed in future flows.

Warther (1995) use aggregated fund flows data provided by ICI, including the flows on equity, bond and precious metal funds. OLS regressions are used to regress flows on the lagged and contemporaneous returns on corresponding assets. The result show that returns are strongly positively correlated with contemporaneous flows but negatively correlated to past flows. Meanwhile, flows are shown to be very persistent. The author removes the predictable part in contemporaneous flows using an AR(3) model and still find a strong positive relationship between flows and returns. He argues that the negative correlation between returns and lagged flows is artifact of persistence of flows, thus should not be considered. This means that the feedback trader hypothesis is not supported. When unexpected flow act as dependent variable, the investors are found to be trading contrary to lagged returns but positive to contemporaneous returns, a finding which is also against the feedback trader hypothesis. The methodology in this paper to separate flows into expected and unexpected part is innovative since it resembles an instrumental variable approach. When this instrument is used, the true relationship between flows and returns are revealed.

Warther (1995) is also an inter-asset study, which paves way for later studies exploring behavioural factors from flow between asset classes (Goetzmann, Massa and Rouwenhorst 2000; Ben-Rephael, Kandel and Wohl 2012) or asset allocation of individual investors (Jank 2012; Chalmers, Kaul and Phillips 2013). The result in Warther (1995) is that flows of bond fund, money market funds and precious metal funds are also correlated with return.

Gruber (1996) relates the return persistence in mutual fund return to the return-performance relationship. He argues that most open-ended funds do not price their services in par with their tracking record (the documented inverse relationship between fee and future performance) and the NAV of the mutual funds do not reflect the inherent manager ability. As manager ability brings consistent future performance, if any investors are aware that this factor is not priced, flows will be persistent to the same extent as performance. It will be reflected as a positive flow-return relationship. The philosophy of Gruber (1996) is similar to the bonding-process proposed by Ippolito (1994). Gruber regress percentage flows on four factor alphas (contemporary and lagged) and lagged return, and the coefficients are all positive significant.

Concerned with a potential downward price spiral caused by mutual fund flows, Remolona et al. (1997) examine the impact of flows on asset market. They utilize the monthly aggregated measure by ICI and separate the fund flows into an unexpected part and an expected part. Their findings are similar to Warther (1995): For both stock and bond funds, unexpected flows are highly correlated with asset returns. The correlation of expected flows with asset returns is indistinguishable from 0. However, they argue that the correlation still does not reveal the causations. It is possible that the return and flow are both driven by a third factor, for example economic factor or investor sentiment, or there is only a single sided causation. With only single sided causation in place, there is only one-way feedback between the mutual fund market and asset market. In this case we should not worry about a downward spiral. In an attempt to capture the pure effect of flows on returns, Remolona et al. (1997) also utilize the instrumental variables. They obtain the fitted return by regressing asset return on some economic variables that is believed to affect expected return but not affected by flows. Flows are then regressed on fitted returns. They find that the innovations in asset return are not correlated with flows, both statistically and economically, as shown in Figure 1-2. As the fund objective gets more conservative, the sensitivity of flow to return gets larger. No explanation has been given, leaving a space for future research.

The methodology by Remolona et al. (1997) suggest that the flow-return relationship may be contaminated by macro variables. Flows and returns respond to a same set of shocks and simple regression suffer from omitted variable bias. This pose a challenge to the result by Warther (1995). However, the result in Remolona et al. (1997) suffers from weak instrument problem, since the monthly return are hardly explained by any realized macro variables. In addition, whether contemporary macro variable influence flow is not clear yet.

Edwards and Zhang (1998) conducts a similar study. Apart from the hypothesis of Warther (1995), they also argue that the informed trader theory, which assume flow contains information to be priced in stocks, is hardly acceptable because mutual fund investors are mainly small, uninformed investors. Their characteristics match the description of noise traders by Delong et al. (1990). This is one of the first mentions of investor heterogeneity in the flow-return relationship study. Many other possibilities have been opened if we treat mutual funds investors as a separate group of investors that behave differently. These heterogeneity brings about different willingness and capability to shoulder risk, different degree of information asymmetry and different investment horizons. Edwards & Zhang (1998) utilize granger causality test and instrumental variable. From a simple VAR system of lag 4, They find no meaningful causality from equity and bond funds flow to returns. The causality is proved to run in the reversed direction. In a robust test, they try to use instrument variables to purge the endogeneity from return and flows. Three macro variables are chosen for returns and two variables concerning purchase power of fund investors are chosen for unexpected fund flow.

A 2SLS regression is run for unexpected flow on orthogonalized returns. After using all contemporaneous information, return still significantly predict flows. It is consistent with results from Granger causality test.

Being supportive of the feedback trader hypothesis, the fact that returns lead flows suggests some degree of return chasing behaviour by fund investors. This is opposite to the findings of Warther (1995) in which investors show somewhat contrarian behaviour.

Santini and Aber (1998) believes that the rejection of Feedback Trader Hypothesis by Warther (1995) is due to the deletion of observations of 1987 market crash. They used a more symmetric sample which is also longer. In addition, they explore other variables that may affect money flows. In this case, the use the level of both short-term and long-term interest rates, performance of mutual fund industry and income level. Performance of fund industry is a risk adjusted measure which differ from Warther (1995), in which raw return is used. The authors are hoping to capture the effect that some investor may refer to some sophisticated performance measure. The results are as expected: New money flows were negatively related to the real long-term interest rate, and positively related to stock market performance and personal disposable income. After controlling for interest rate, performance and income, there is still no sign of feedback trading. Investors do respond to performance of any type. Their result may simply reflect the rational expectation of fund investors. Two of the variables used as controlling variables, interest rates and shocks to income are all important state variables that predict future consumption. Putting those variables in the equation is similar to the instrumental variable methodology used by Remolona et al. (1997) and Edwards and Zhang (1998), given the fact that these are proved to be weak instruments in a flow-return relationship.

Fant (1999) has more implication for investor heterogeneity. He notes that the two different components in ICI aggregated flows, exchange in/out and sales/redemptions reflect decisions by different group of investors. The group of investors that is more sensitive to risk, having liquidity concerns, or having a shorter investment horizon will seek to migrate to another asset class through exchange in-out when facing changing market conditions since there arguably less frictions in exchange in/outs. When investors transact through sales-redemption, they move between fund families by paying some costs. The group of investors that have longer horizon is expected to go with sales/redemptions. Thus, exchange in-outs should be more sensitive to market conditions than sales/redemptions.

When breaking flows into four components, Fant (1999) support the existence of friction by showing there is less autocorrelation in exchange in-outs. In addition, only exchange in-outs are responsible for the positive correlation of flows and returns in Warther (1995). Beside the evidence on contemporary relationships, there is still little evidence on a lead-lag relationship.

The study of Fant (1999) shed light on our study. The important role of exchange in/outs reveal that mutual fund is not simply a long-term buy-and-hold strategy for investors. Instead, mutual fund is an important channel to undertake tactical asset allocation or market timing. Mutual fund exchanges offer more mobility and liquidity for these actions than purchase and redemptions, since the transaction cost and time consumption is lower. To prove, the VAR result show that only the exchange-outs are related to lagged return. The author also reports that the sign of the coefficient on lagged returns are negative. Market timers seems more impatient to hold mutual fund than to hold cash when facing market returns. The different behaviour of the exchange channel from sale/redemption channel reveals some degree of investor heterogeneity among mutual fund investors: some vigilant investors time the market on conditional risk premia while other investors tend to stay put.

1.2.2.2 Non-linearity in Flow-Performance Relationship

The above studies focus on the average flow-return relationship. The final interpretation depends on the overall direction and magnitude of the relationship. However, few studies at that time focus on the shape of the function. Many later studies find that the flow-return relationship is convex, that is the rate that returns attract flows is higher in the high return region. In comparison, flows' response to negative return is relatively flat. While a positive relationship between flows and return has been a de facto consensus, many successors aim to identify structural patterns in this relationship and give economic justifications and implications.

Chevalier & Ellison (1997) discovered non-linearity in flow performance relationship using a non-parametric model. The regression of flow on performance measures plus control variables are similar to previous study. However, they let the estimates to be performed on sub-samples to capture the conditional difference in slopes. The results show that the contemporaneous coefficient on fund returns are steeper for best performers and nearly flat for worst performers. In addition, the younger funds have higher return sensitivities than elder funds. Chevalier & Ellison (1997) does not try to explain why the relationship is non-linear. Instead, they explore what this relationship may bring to the fund companies. They propose that as the revenue of the fund companies solely depends on the size of their AUM rather than return, their strategy may be biased towards increasing their AUM to maximize profits. The shape of the relationship implies that mutual funds can adopt an investment strategy that increase the volatility of their portfolio, since flows responds more sensitively to extreme positive returns than to extreme negative returns. Concerning the excess sensitivities on young funds, Chevalier & Ellison (1997) explain that younger funds has relatively short track record so that the excess sensitivities represents customers adjusting their evaluation on manager ability.

The result of Chevalier & Ellison (1997) shows that the decisions of mutual fund investors induce the convexity in flow-return relationship, which incentivize mutual fund companies for their window dressing behaviour. Thus, the authors suggest a comparison between the evaluation process between retail investors and institutional investors.

In response, Guercio & Tkac (2002) look into both pension funds and mutual funds. They argue that while mutual funds are bought and sold by retail investors who are guided by nobody but their own, pension funds usually have a trustee committee comprised of professionals. These professionals may make more rational decisions, which reduce the flow-return convexity. In comparison, retail investors flock disproportionally to good performers while failing to punish bad performers. More evidences support Guercio & Tkac (2002)'s arguments. They find while retail investors are more concerned with unadjusted raw return, pension fund flows are strongly correlated with adjusted return like Jensen's Alpha and Sharpe Ratio, and the relationship is symmetric in the high and low return region. The findings of Guercio & Tkac (2002) and Chevalier & Ellison (1997) not only suggest that the evaluation process of institutional and retail investors differ, but also suggest that managers can maximize new cash flows by adopting specific strategy.

Karceski (2002) follow Chevalier & Ellison (1997)'s discovery of year end window dressing. They provide explanation on the emergence of literature since 1970 that prove CAPM wrong. These literature usually show a failed CAPM: beta is barely associated with cross-section of average stock returns, and CAPM failed to provide convincible goodness-of-fit. The author argue that mutual fund competition encourage fund companies to engage in window dressing, the gambling behaviour characterized in Chevalier & Ellison (1997). To increase the volatility of their portfolio, fund managers increase their exposure on market risk. As a consequence, high beta stocks receive high inflows from managers, reducing their expected return. Although the study is not directly related to flow-return convexity, it shows the consequence of this convexity. In addition, it provides a unique perspective on the linkage between fund market and equity market.

Sirri & Tufano (1998) believes the problems lies in searching cost. They argue that as trained professionals select funds using their financial knowledge and resources, mutual fund investors are not able to spend as much time. These unprofessional investors depend highly on signals that convey the quality of the fund, such as past return, advertisements or media coverage. Due to bounded rationality of investors, these signals put a fund in the consideration set for these investors. Thus, the authors predict that fund that exert more efforts in delivering these signals will experience higher flow-return sensitivities. In addition, since past return is also a salient product characteristic, investor will flock to (or flee from) funds with good (bad) track records. The convexity is created by these non-linear behaviours. Sirri & Tufano (1998) proxy search costs for a fund using three characteristics: company size, marketing costs and media coverage. The result show that flow-return sensitivities are much higher in high fee funds, probably because these funds put more efforts in marketing practices. The sensitivity also depends on media coverage. Controlling for fund size, funds with more media citations exhibit higher flow-return sensitivities.

The study of Huang et al. (2007) is of similar spirit to Sirri & Tufano (1998). Huang et al. (2007) generalize all cost incurred to investors in spotting a fund and add it to their financial portfolio as participation cost. The participation cost includes a cost for information and cost for transaction. These costs raise the barrier for investors to invest in a fund. The authors predict that transaction costs alter the flow-return relationship. First, different transaction cost cause funds to accommodate investors with different degree of sophistication. When participation cost is high, investors refers to the cheapest source of information – historical return to yield investment decisions. This explains the high region of the convexity. Second, transaction cost hinder migrations between funds. Funds with larger transaction costs make investors cautious when they are in middle return region. This explains the middle part of the convexity. The study finds higher sensitivity in middle return region and lower sensitivity in high return region for funds with less participation cost. Their model not only validates the hypothesis of Sirri & Tufano (1998) again, but also explains the reason why different region of flow-return convexity may be so.

Jain & Wu (2000) provide evidence on the relationship between advertisements and fund flows. They find that advertisements greatly attract flows. This supports Sirri & Tufano (1998)'s arguments that advertisements lower the search cost f customers. However, the authors do not rule out another possibility: fund managers advertise only because they want to attract new money, instead of lowering the participation cost of investors. Thus we should be aware of the positioning of future studies related to the non-linearity of flow-return relationships: studies like Sirri & Tufano (1998)and Huang et al. (2007) examine the what perceptual pattern of investors may have caused the convexity, while studies like Chevalier & Ellison (1997) and Jain & Wu (2000) focusing on the response of management companies with regard to this convexity.

Lynch & Musto (2003) believes the non-linearity of flow-return relationships originates from managers instead of its customers. They argue that the flatness in the bottom performance region comes from the decision of fund management companies to replace personnel or strategies following a poor return. Investor will be less willing to move away from funds with bad performance since they foresee change of strategies, resulting to convexity. This view differs from past studies in which personnel and strategies remain constant. A constant personnel or strategy imply that past performance is a consistent predictor of future performance. If we assume return chasing, all non-linearity will be emanated from investors. When we release the static assumption, personnel or strategy change will have a material influence on flow-return relationship by altering investor expectations. Lynch & Musto (2003) argue that strategy change can be proxied by change in factor loading and manger replacements of a fund. They find that strategy almost always change after a bad performance. Lynch & Musto (2003)'s findings also join the literature on performance persistence I discussed in the last section. Under their assumption, persistence is short-lived because managers compete for better performance. Bad managers are motivated to change their investment strategy to adapt to the competition. However, all of these arguments rely on strong assumptions: new strategies are no worse than old strategies, and customers always believe in this changes may bring boost on performance.

Berk & Tonks (2007) relate the persistence of poor performing funds to the flatness of bottom return region of flow-return function. They notice that new money can decide to enter in to a fund at any time when investor find that fund to be favorable. However, only existing customers can withdraw funds when performance is poor. Empirical evidence in their study show that the sensitivities of flow to return is conditional on the time the fund has stayed in the bottom decile. Their arguments is similar to Christoffersen & Musto (2002). Coincidentally, the two studies discovered a selection mechanism that eliminate performance sensitive investors from poor performing funds. While Christoffersen & Musto (2002) examine its implication to the pricing of funds, Berk & Tonks (2007) examine its implication to the non-linearity of flow-performance relationship.

An emerging strand of literature relates the convexity issue to the sophistication of investors, for example Huang et al. (2012) and Ferreira et al. (2012). Huang et al. (2012) emphasize the importance of second order effect of return. They document a “dampening effect”, where extreme volatility of fund track record disrupt investor from inferring skill information. However, this quality seeking process, similar to one described in Ippolito (1992), are assumed to be conducted only by sophisticated investors. Unsophisticated investors (proxied by fund load, fund type and star fund status) are assumed to chase return blindly. The empirical evidence shows that only sophisticated investors are subjected to the dampening effect.

Ferreira et al. (2012) compare the shape return-flow function across world markets. Similar to Huang et al. (2007), they acknowledge the difference in investor sophistication and the dependence of convexity on sophistication. Advertisements are believed to be the cause, since they steer the attention of unsophisticated investors from the poor performers to recent best performers. The authors find that financially and regulatory developed countries has less degree of convexity. In support to Huang et al. (2007), they also find that higher participation cost is associated with lower sophistication and higher convexity.

Based on the literature reviewed above, the only consensus is that mutual fund flows are positively associated with past fund returns, and this relationship is characterized by a convex function which is steep on the high-performance region and flat on the low performance region. There are various interpretations on the convexity of the function, which are sometimes exclusive. The rational campaign argues that strategy transition or information asymmetry to be the underlying factor, while behavioural campaign highlight the role of bounded rationality of mutual fund investors. At the very least, whether there should be any relationship between return and performance is yet to be answered, since this correlation seems to defy efficient market theory.

Other possibilities can be explored, for example the disposition effect documented in behavioural economics. The disposition effect is a phenomenon that investors are quick to realize paper gains and slow in realize losses, and Kahneman & Tversky (1979)'s prospect theory lays the theoretical ground. The disposition effect fit exactly the pattern of the flow-return relationship in mutual fund market, yet no attempt is made on this direction. The issue will be discussed at length in later section and I will dedicate the second Chapter in exploring this possibility.

1.2.3 Smart Money Versus Dumb Money

Whether mutual fund investors succeed in their fund investment is a hot topic in the field. Although success is defined on many dimensions, it generally entails the examination of a causal relationship: the mutual fund favored by investors should deliver higher than average performance *ex post*, and the mutual funds dumped by investors should exhibit lower than average performance later. An investor (or group of investors) is "smart" in that their direction of investments predicts future performance of asset of the same direction so that their decisions are rewarded. The "dumb" investors are defined the opposite. Hence the Smart Money Effect and Dumb Money Effect. I do not specify the exactly measure of performance since it depends on personal perception. Thus, different measures like gross-return, risk adjusted return and net-of-fee return should be examined parallel.

The answer to the question sparks curiosity since it has special bearing on both rationality-based economics and behavioural finance. Smart money effect is supportive to the prediction of traditional finance which generally assume that every investor forms optimal, homogeneous expectation by utilizing all available information. In contrast, behavioural finance predicts individual deviates from these paradigms and make erroneous investment decisions. Clearly, it would accommodate a dumb money effect. As a compromise, one could also say that smart and dumb investors co-exist, and that they are rewarded (penalized) accordingly. This story will not violate market efficiency since it still allows the market to be a zero-sum game.

The smart or dumb debate is not restricted to performance of the fund. Another aspect is pricing of the fund. Mutual fund managers charge investors a fixed or one-off fee for their service, with a mission to fulfill their investment targets. The relationship between future performance and pricing of mutual funds determines whether these charges are reasonable. Smart investors will select an appropriate combination of fees and performance to optimize their investment outcome, since fees will eventually contribute to their bottom line. While there is dedicated literature on fund fees, many smart or dumb money paper recognize this issue and select after-fee performance measure.

1.2.3.1 Smart Money Effect

Early literature has found a smart money effect. Two iconic papers are Gruber (1996) and Zheng (1999). Gruber (1996) examine if new cash flows into the fund earn higher return than usual as part of an attempt to solve the puzzle why investors would buy active managed funds, even if finance theory suggests a buy-and-hold strategy. He argues that the quality of the manage is not included in the NAV of the fund. This creates a persistence in mutual fund returns as investors recognize the manager quality and continuously price this merit in. If it is the case, new money into funds should earn higher risk-adjusted return, new money out of funds should earn lower risk adjusted return, which validate their previous judgements. If the opposite is true, the marginal decision of investors will be systematically erroneous, similar to what Ippolito (1992) described as a “degenerating equilibrium”. Thus, three conditions would support his proposal: There is return persistence; the flows should be as predictable by some metric as return; flows should in average identify better funds *ex ante.*

Gruber use weighted four-index alpha as a metric for performance. Then he calculates the alpha of fund portfolios weighted by previous cash flow. The results show that positive alpha follow positive cash flows and negative alpha follow negative cash flows. The results are robust on measures of cash flows and the weighting scheme. Based on the result, Gruber (1996) demonstrate the potential existence of two clienteles: a sophisticated clientele and a restricted clientele. The sophisticated clientele has the essential knowledge and rationality to identify good funds. The restricted clientele does not have the same knowledge set or is restricted from trading funds. A direct consequence is that new money outperforms the stock of money.

While Gruber (1996) does not specifically examine the smart money effect, the study of Zheng (1999) provides more evidence on the effect. Zheng (1999) confirms that the funds that attracts money performs better than funds that lose money. In addition, small funds with positive recent cash flow are able to beat the market, though not so for all funds with positive recent cash flows (a size effect). The smart money effect is also short-lived: the information identified by these new investments are fully priced in after 30 months. He also explores the possibility that this smart money effect may be attributable to betting on winners. This is not the case since winning funds contains a proportion of past winners which is not statistically larger than zero. This means investors favor past winners just as much as last losers. The past winners contribute only 30% of the smart money profit. In a latter robust test, the author shows that the relationship between past flow and future return is not spurious: the addition of a set of macroeconomic variables and style dummy do not destroy the predictability. This is a sign that the smart money effect is a result of investors identifying fund-specific information.

Keswani & Stolin (2008) documents a robust smart money effect in UK. Apart from the familiar result that funds with new money perform better than average, the authors also find that this is true for both institutional and retail investors. The classification is convenient for UK data since the IMA database they use identify institutional or retail flows. Unlike Zheng (1999), they find smart money effect on all funds, instead of only small funds. Another difference is that smart money effect in UK last for only 4 months, compared to Zheng (1999)'s 30 months. The result is also robust to return persistence as they adjust performance using an additional momentum factor. An interest finding in Keswani & Stolin (2008) is that only buy decisions show a smart money effect. They believe it to be the result from the disposition effect, a phenomenon that individual buy decisions are more rationally made than sell decisions.

Berggrun & Lizarzaburu (2015) examine the Brazilian fund market. While they do not find an overall smart money effect, flows of small and retail funds do show some smartness

1.2.3.2 Dumb Money Effect

Contrary to "Smart Money Effect", "Dumb Money Effect" means investors past decisions yield low future returns in average, either measured by gross return, risk adjusted return or after-fee net returns. There are various interpretations for the dumb money effect. While many attributes it to behavioural bias of fund investors like heuristic bias, narrow framing and overconfidence, rational explanations have also been offered. For example, it is found in Gruber (1996) that the stock of money has poorer performance compared to the flow of money. As the author champions the idea that investors are smart in manager selection, he attributes the bad performance of stocks of money to the existence of a "restricted clientele". This restricted clientele is described as facing certain institutional and tax disadvantages so that they constitute the stock of money.

A class of study concentrate on the implication of fund/stock momentum on the smart vs dumb debate. While fund return persists, investors is able to exploit these price momentums. When their performance is measured before momentum, the investors act as if they are beating the market. From the perspective of managers, they may be adopting a simple winner-picking strategy as if they have true ability. This class of study believe that the momentum riding profit should be deducted from the performance of both mangers and investors to yield true evaluation. When momentum is adjusted, we may yield different result. The dumb money literature reviewed in this section agree that smart money effect is an artifact of price persistence. I will dedicate a whole section to behavioural and other explanations.

Carhart (1997) is the first to consider price persistence in performance evaluation of investors. He finds that the persistence in fund return is explained by momentum itself instead of manager skill. Although his perspective is from the managers' which differ from my study, he partly answers whether the persistence in mutual fund performance is explained by factors other than manager ability. He includes a one year momentum factor based on the finding of JEGADEESH & TITMAN (1993) in risk adjustment, which inspires many later studies on price momentum and industry practitioners. The idea of Carhart (1997) is that the persistence in mutual fund performance is either a true reflection of manager quality or an omitted variable problem. Gruber (1996) describes that price persistence is created because manager ability is not priced in fund NAV. When investors recognize this, money flows into good funds and flow out of bad funds, creating price momentum.

The case in Gruber (1996) tells only the former story but not the later. When a momentum factor is included in the risk adjustment, Carhart (1997) find that the return persistence almost disappears, except for the extreme bad performance region. What's worse is that managers do not seems to follow momentum strategy: their momentum profits are almost entirely attributed to luck. He also finds that other part of the persistence not explained by momentum is due to transaction cost, measured by a variant of turnover, and liquidity, measured by sensitivity to a liquidity mimicking portfolio.

Inspired by Carhart (1997), Sapp & Tiwari (2004) examine if the smart money effect of fund investors is attributable to stock momentums. The methodology of Gruber (1996) and Zheng (1999) to weight portfolio based on their last period flows is replicated. The difference is that they adjust the inflow-outflow portfolio return by and additional momentum factor. When the one year momentum factor is included, the excess return on these portfolio dissipates. Sapp & Tiwari (2004) envisage two potential explanations to this phenomenon, similar to Carhart (1997). The first is investors intentionally adopt a momentum strategy which weight up recent winner funds and weight down recent loser funds. The second is investors chase fund return blindly. Thus, they perform a test on this two hypothesis. Sapp & Tiwari (2004) argue that the former requires investors to be sensitive to the momentum loading of the funds while the latter requires investors to be sensitive to the recent extreme return. The result shows investors is sensitive to the extreme return, so they are chasing return blindly. Sapp & Tiwari (2004)'s finding is a blow to Gruber (1996).

Lou (2012) find that the momentum in fund return is the result of investor purchasing behaviours. He documents a price pressure effect in which fund investors' decisions force managers to expand their existing positions, creating continuation in price. Since these funds stays in marginal investors' portfolio, both the manager and investors enjoy momentum profits. Their characterization of dumb money effect is slightly different to Sapp & Tiwari (2004). Sapp & Tiwari (2004) focus on the implication of price momentum on performance evaluation while this study treats momentum profits of investors as self-fulfilling.

The innovation in Lou (2012) is the definition of a new variable which capture the flow-induced trading, FIT. FIT is the aggregated mutual fund trading in a stock attributed to flows rather than information. Higher FIT indicates higher proportion of stock trading volume initiated by fund investors. He then aggregates all expected components of flow induced trading to form E(FIT), which captures flow induced trading for a stock from all funds. The smart money hypothesis states that funds with lagged inflow outperform funds with lagged outflows, while price pressure story in this study predicts that funds with higher E(FIT) outperform. Thus, Lou (2012) sort funds into 25 portfolios by both E(FIT) and lagged return. Only long-short strategy formed by E(FIT) deliver statistically significant excess return. However, using this methodology constrain the time horizon to a quarter. In a later cross-sectional regression of quarterly fund returns, they also find that E(FIT) subsume flows.

There are evidences on dumb money effect in other parts of the world, yet their methodologies differ. Feng et al. (2014) test the smart money effect in China. The Chinese datasets distinguish between institutional and retail investors. Their findings are institutional investors are able to identify future good performers while retail investors exhibit a dumb money effect. They emphasize the importance of distinguish between institutional and non-institutional investors. Berggrun & Lizarzaburu (2015) document dumb money effect in Brazilian mutual fund market except for small and retail funds.

Keswani & Stolin (2008) obtain unique UK dataset that separate institutional and individual fund transactions. Feng et al. (2014) obtain a similar Chinese dataset that distinguish institutional and individual investors. They find that only institutional investors exhibit smart money effects. Akbas et al. (2015) recognize average mutual fund flows as smart and hedge fund flows are dumb. They find that several well-documented financial anomalies are deteriorated by mutual fund flows but attenuated by hedge fund flows. Thus, they are in a position to conclude that average mutual fund investors do not act in a rational way.

1.2.4 Fee Choices

Another attractive issue in fund study is the relationship between fund investments and the pricing for funds, the fees paid to managers. As a service, active portfolio managers are delegated to optimize investment performance of investors. The traditional view of the role of fees are that they serve as a cost to search for valuable information. The market is expected to be informationally efficient in a way that these cost will equate the abnormal return of portfolio managers in equilibrium Grossman (1976); Grossman & Stiglitz (1980). Under this view, before-fee alpha of funds should at least justify their fees. From the supply side, managers equipped with better skills should be able to demand a higher mark-up. Under asymmetric information, pricing could be used as a signaling mechanism for managers to signal their true ability Sirri & Tufano (1998). Under this assumption, fees of funds should not only justify their *ex post* alpha, but also predict future net-of-fee alphas (as opposed to gross alphas). In other words, net-of-fee alphas convey management qualities.

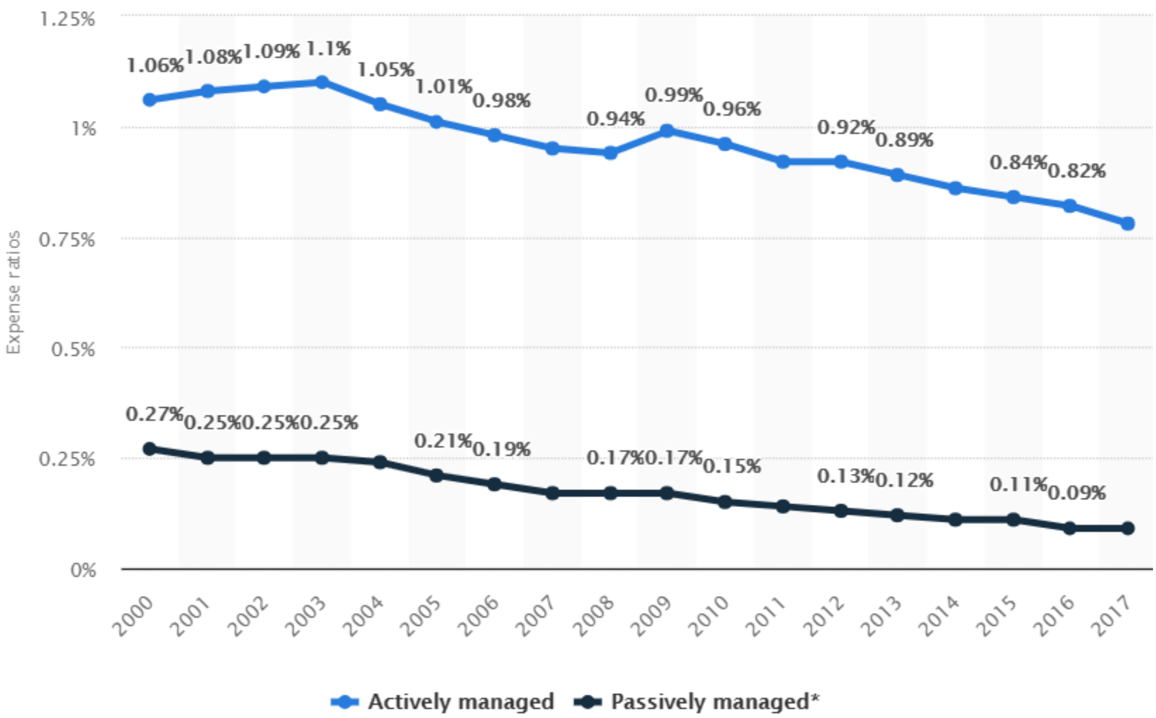


Figure 1-3 Expense ratios of equity mutual funds worldwide from 2000 to 2017, by fund management type

Source:Statista, 2018

Figure 1-3 shows the average expense ratios paid by worldwide investors. Two trends can be observed from the graph: the sustained decline of the fees and the vast difference in fees for actively and passively managed funds. The decline in fees can be explained by competition, as the number of funds in US alone went from nearly 1,000 in 2000 to nearly 10,000 at end of 2017. It can also be explained by managers' strategic setting facing gradually more educated clinteles. Despite the decline, the 17.5 trillion total net assets of mutual fund in US (measured as of end of 2017) still guarantee manages a very healthy amount of rewards. The difference in fees of passive and active funds remind us the massive benefits one can earn from switching to passive investments, as discussed in Chapter 2 and Chapter 4.

A disheartening truth for investors is that higher fees do not buy superior managers. It is widely documented that fees are neither a good determinant nor predictor for performance. Fees are even found to be negatively related to performance measured in various ways. Ippolito (1992) found that during 1966-1983, fees of funds barely explain their CAPM alpha. He later checks the investment fee formulae for 373 funds and failed to find a significant number of funds that adopt incentive fees. Thus he cannot support the notion that fees contribute to after-fee alphas. Elton et al. (1993) examine the information efficiency of mutual funds market. Unlike Ippolito (1992), they use a multi-index model that incorporates non-S&P 500 stocks and bond index. They find that fund failed to outperform these benchmarks. Among all the funds, ones with the highest fees and turnovers underperforms cheaper and low turnover peers. In addition, bad funds do not lower fees and good funds do not raise fees in time, contrary to the prediction of signaling story. Gruber confirms the findings of Elton et al. (1993). He finds that the top performing funds in terms of alpha charge only average fees. The worse performing funds charge higher average fees. Again, these winner and loser funds do not change fees with regard to their track record. Carhart (1997) adjust return using an additional momentum factor. His works show that expense ratio is a significant negative determinant for four factor alphas. Moreover, load funds significantly underperform non-load funds. Sirri & Tufano (1998) argues that mutual fund industry is too big and complex for individual investors. Fees may correlate with marketing spends (the signaling) of management firms to lower search cost of consumers. He discovers that consumer is more aware of the track record of funds only when fees of funds are high. However, his study only shows that management firms are motivated by higher fees to attract more flows. It does not tell investors can be better off by selecting higher fee funds since previous evidence do not suggest so. In fact, higher advertisement spending is found to be negatively related to future performance of fund in Jain & Wu (2000).

High fees seem to be a consistent indicator for bad funds, which is puzzling. Scholars thus suggest fee choice are somewhat related to investor sophistication. One explanation is that fees are the result of different distribution channels. Unsophisticated investors, often financially uninformed, may rely on advisors or advertisements instead of own judgements to form investment decisions. These channels, arguably costly, is associated with higher fees (Bullard et al. 2008). Another explanation is share class. Large management companies tend to design different share classes to cater to various needs of investors. It is not uncommon that management companies fine tune their allocation of load fees, marketing fees and periodic expenses according to investor profiles to generate maximum economic rents (Christoffersen and Musto 2002; Bullard, Friesen and Sapp (2008); Gil-Bazo and Ruiz-Verdú 2008; Nanda, Wang and Zheng 2009). Gil-Bazo & Ruiz-Verdú (2009) refer this as strategic fee setting.

Chapter 2

Stay Put, Stay Cheap – A Review of Mutual Fund Investor's Real Performance

Chapter 2 - Stay Put, Stay Cheap - A Review of Mutual Fund Investor's Real Performance

ABSTRACT

This chaper investigates several previous propositions on behaviours of mutual fund investors, based on investor learning. The performance of fund selection, fee selection and market timing ability are examined on deciles of proxies for investor sophistications. The most sophisticated investors by my measure show advantage in selecting funds with better risk adjusted return and lower fees. however, they also have significant higher performance gaps, a measure of bad timing ability. I also show that sophisticated investors can optimize timing performance from trading less.

2.1 Introduction

A debated topic in mutual fund study is whether investors make rational decisions in investing in mutual funds. By rational, I mean that investors are able to achieve the desired outcome by incorporating the right funds into their portfolio. A success fund investment should maximize after-fee return on a designated level of risk. While many investors in US choose to reside in low-cost, benchmark-tracking vehicles like Exchange Traded Funds, most of them prefer actively managed funds ICI (2016). Standard financial theory suggests that security selection and market timing are two material components of active investments Fama (1972). The first component corresponds to whether investors are able to find skilled managers so that their funds provide superior risk-adjusted returns. The second component concerns if investors can foresee fund performance and choose to enter/exit a fund. As fund managers must be compensated for their services, fee is a third aspect that contributes to their bottom line.

Past papers on the rationality of fund investors approach the question by investigating the three stated criteria separately. The first tranche aims at examining whether investors choose fund with higher risk adjusted returns *ex ante* in an effort to earn abnormal profits in terms of equilibrium benchmarks. Thus, this is to say, whether they are able to identify superior managers. There are mixed evidences on this issue, which are often epitomized as a “smart” and “dumb” money debate. Gruber (1996) and Zheng (1999) find that fund portfolios weighted by flow perform better than a value weighted portfolio. Thus, they conclude that marginal investors are in average smart. However, studies like Carhart (1997), Sapp & Tiwari (2004) and Frazzini & Lamont (2008) perplex the smart money effect. While these papers address the average performance of marginal investors, this study is slightly different that it examines the cross-sectional fund selection ability. Echoing the finding of Fama & French (2010) that there is cross-sectional dispersion in manager skills, I show a cross-sectional dispersion in fund selection skills.

The second tranche looks at fee choices, which is whether managers price their funds reasonably and whether investors are able to choose the most fee-efficient funds. Two typical papers are Christoffersen & Musto (2002) and Gil-Bazo & Ruiz-Verdú (2008). A common finding in these papers is investors differ in fee choice. In addition, not all investors choose fee rationally. Funds with high fee and bad performance may survive for a long time. The muted sensitivity of flows to performance in the low performance region is a potential manifestation of this issue. Carhart (1997) finds a negative relationship between load fees and abnormal return, and funds with high load fees survives in sample for a long time in average. Gil-Bazo & Ruiz-Verdú (2008) finds a puzzling negative relation between before-fee risk-adjusted performance and fees in a sample ofU.S. equity mutual funds and they explained with the unsophistication of investors not responding to high fees. My study also tackles this issue.

The third line of study focus on the timing decision of mutual fund investors. Standard market timing model posit that good timing optimizes the investment performance in a way that an individual increases his bet prior to upward movements of market and withdraw funds before downward movements. Mutual funds flow, reflecting innovation in mutual fund demand, is a convenient workhorse for this line of study. If in average, inflows predict positive fund returns and outflows predict negative fund returns, investors are deemed to perform successful timing.

However, little study seems to relate the three distinct dimensions of mutual fund investments. Fees, risk adjusted returns and timing constitute a complete investment process. The rationality of investors cannot be assessed by any of the three criteria alone. The study is the first to try assessing the performance of mutual fund investors by all three criterions. I find that there are distinct cross-sectional dispersions in fund selecting, fee choosing and timing abilities. More importantly, the three abilities are correlated but not identical. For example, investors who are particularly good at fund selection do not necessarily possess superior timing ability, if not inferior. The following sub sections review the previous literature while illustrating my results accordingly.

2.1.1 Fund Selection

Fund selection have been characterized as a quality seeking process. Investors are believed to be choosing among thousands of largely homogeneous services offered by managers, of whom the ability to generate abnormal return differ. Thus, the inherent quality of funds is determined by the managers. There is a long tradition to use alpha as a proxy for managerial ability (see Carhart 1997; Gruber 1996; Wermers 2000; Kosowski et al. 2006; Fama & French 2010). Ippolito (1992) argue that alpha reflect the quality of the fund and rational investors should be able to react to information regarding the alpha of the fund. Indeed, he finds that investors have been successful in identifying good quality funds. In the long term, good quality fund will be supported by new money and survive. Gruber (1996) finds that the risk adjusted return on fund portfolio weighted by new money ex ante are higher. He argues it is a sign that average mutual fund investors are smart in fund selection. Using a similar methodology, Zheng (1999) confirms the findings of Gruber (1996). Jointly, they attribute these findings to a "smart money effect".

However, many later studies points to the contrary, namely "dumb money effect." Wermers (2003) questions the previous finding by proposing a scenario where inflow and out flow result to return momentum. The momentum separates winning funds and losing funds further, resulting to erroneous judgement that investors are smart in advance. Sapp & Tiwari (2004) confirm this conjecture by using a four-factor model as risk adjustment. The additional momentum factor explains away the short-term abnormal return of investors. Using fund portfolio holding data, Sirri & Tufano (1998) construct a measure of incremental stock holding initiated by new purchase and redemptions. They show that the return on stocks bought by funds underperform that sold by funds. Lou (2012) construct a measure of flow-induced return for stock. Past return of the stock included in fund holding no longer predict future return when accounting for these flow-induced returns. What's worse is that the returns reverse in longer horizon. Thus, mutual fund flows contribute nothing but price pressure.

Whether mutual fund investors are dumb or smart, the above study fails to answer one question. They only show whether fund investors are able to earn risk adjusted return *in average*, but not which group of investors is more likely to pick better funds. Several study propose qualitative measure of investor sophistication that correlated with potential fund selection ability. Capon et al. (1996) design a survey to discover the underlying factors for mutual fund purchase. They find that only a small group of investors know relatively sufficient for their investment. Many investors are perplexed by section criterion that is unrelated to financial performance, like advertisements and advisor recommendations. Thus, they suggest the existence of a small group of highly sophisticated investors. Other studies rely on self-reported data. For example, Keswani & Stolin (2008) obtain unique UK dataset that separate institutional and individual fund transactions. Feng et al. (2014) obtain a similar Chinese dataset that distinguish institutional and individual investors. They find that only institutional investors exhibit smart money effects. Akbas et al. (2015) recognize average mutual fund flows as smart and hedge fund flows are dumb. They find that several well-documented financial anomalies are deteriorated by mutual fund flows but attenuated by hedge fund flows. Thus, they are in a position to conclude that average mutual fund investors do not act in a rational way.

In this study, I propose a measure of potential fund selection ability based on consumer behaviour theory, the sensitivity of investment flows to return residuals. Ippolito (1992) links fund investment to quality seeking process in commodity market. They argue that the performance residuals convey information on quality of managers. As long as manager quality differ, fund will exhibit serial correlation in performance residuals. Thus, the rational learning of investors imposes some sensitivity to this measure of performance. In long term, as superior managers obtain increasingly higher market share, bad managers will be driven out. The rational learning view can also be found in many other studies, like Lynch & Musto (2003), Berk & Green (2004), Bollen (2007) and Huang et al. (2012).

The rational learning view are supported by two facts. One is the stylized evidence of performance persistence in mutual funds. Early studies by Grinblatt & Titman (1992), Hendricks et al. (1993), Brown & Goetzmann (1995), Elton et al. (1996) already found short-term persistence in both risk adjusted and unadjusted mutual fund returns. Gruber (1996) consolidate the finding. He finds that risk adjusted return predict future performance for a horizon as long as three years. In addition, risk adjusted return is the best among class of potential predictors. Gruber (1996) argues that when recent performance signal future prospect of a fund, flow acting upon recent performance will not be in conflict with efficient market hypothesis, exactly because funds are sold at NAV and manager ability is not priced. This view is similar to Ippolito (1992)'s consumer vigilance framework. The other is the cross-sectional dispersion in manager ability. If managers are equal in ability to create value, there is no point in searching for better funds. Extreme returns happen only because of luck, instead of inherent skill of managers. In this case, investors will be better off holding a diversified fund portfolio to reduce their search costs. However, solid evidence suggests the existence of different manager abilities and the value for digesting better funds. Kosowski et al. (2006) and Fama & French (2010) offer thorough examinations. In their studies, the observed alpha survives different specifications of statistic tests and they are not completely due to luck.

The rationale for my usage of flow sensitivity are obvious. If manger quality differ and consumer exert rational learning to filter out better managers, we would expect sensitive investors (the vigilant investors by parlance of Ippolito 1992) to be able to pick funds with higher risk adjusted returns. Performance insensitive investors or investors with negative sensitivities will end up in worse funds. The performance sensitivity should also be a relative strong explainer of alphas to ensure good managers and bad managers are fully captured by this rational learning process. Given the widely held notion that manger skills differ, it will be interesting to see if some group of investors are able to reside in better funds than others. In my study, it is found to be the case. The performance sensitive investors indeed choose funds with monotonically higher four factor alphas.

2.1.2 Fee Selections

Another attractive issue in fund study is the relationship between fund investments and the pricing for funds, the fees paid to managers. As a service, active portfolio managers are delegated to optimize investment performance of investors. The traditional view of the role of fees are that they serve as a cost to search for valuable information. The market is expected to be informationally efficient in a way that these cost will equate the abnormal return of portfolio managers in equilibrium (Grossman 1976; Grossman and Stiglitz 1980). Under this view, before-fee alpha of funds should at least justify their fees. From the supply side, managers equipped with better skills should be able to demand a higher mark-up. Under asymmetric information, pricing could be used as a signaling mechanism for managers to signal their true ability Sirri and Tufano (1998). Under this assumption, fees of funds should not only justify their *ex post* alpha, but also predict future net-of-fee alphas (as opposed to gross alphas). In other words, net-of-fee alphas convey management qualities.

A disheartening truth for investors is that higher fees do not buy superior managers. It is widely documented that fees are neither a good determinant nor predictor for performance. Fees are even found to be negatively related to performance measured in various ways. Ippolito (1992) found that during 1966-1983, fees of funds barely explain their CAPM alpha. He later checks the investment fee formulae for 373 funds and failed to find a significant number of funds that adopt incentive fees. Thus he cannot support the notion that fees contribute to after-fee alphas. Elton et al. (1993) examine the information efficiency of mutual funds market. Unlike Ippolito (1992), they use a multi-index model that incorporates non-S&P 500 stocks and bond index. They find that fund failed to outperform these benchmarks. Among all the funds, ones with the highest fees and turnovers underperforms cheaper and low turnover peers. In addition, bad funds do not lower fees and good funds do not raise fees in time, contrary to the prediction of signaling story. Gruber confirms the findings of Elton et al. (1993). He finds that the top performing funds in terms of alpha charge only average fees. The worse performing funds charge higher average fees. Again, these winner and loser funds do not change fees with regard to their track record. Carhart (1997) adjust return using an additional momentum factor. His works show that expense ratio is a significant negative determinant for four factor alphas. Moreover, load funds significantly underperform non-load funds. Sirri & Tufano (1998) argues that mutual fund industry is too big and complex for individual investors. Fees may correlate with marketing spends (the signaling) of management firms to lower search cost of consumers. He discovers that consumer is more aware of the track record of funds only when fees of funds are high. However, his study only shows that management firms are motivated by higher fees to attract more flows. It does not tell investors can be better off by selecting higher fee funds since previous evidence do not suggest so. In fact, higher advertisement spending is found to be negatively related to future performance of fund in Jain & Wu (2000).

Until this point, high fees seem to be a consistent indicator for bad funds, which is puzzling. Scholars thus suggest fee choice are somewhat related to investor sophistication. One explanation is that fees are the result of different distribution channels. Unsophisticated investors, often financially uninformed, may rely on advisors or advertisements instead of own judgements to form investment decisions. These channels, arguably costly, is associated with higher fees (Bullard et al. 2008). Another explanation is share class. Large management companies tend to design different share classes to cater to various needs of investors. It is not uncommon that management companies fine tune their allocation of load fees, marketing fees and periodic expenses according to investor profiles to generate maximum economic rents (Christoffersen and Musto 2002; Bullard, Friesen and Sapp 2008; Gil-Bazo and Ruiz-Verdú 2008; Nanda, Wang and Zheng 2009). Gil-Bazo & Ruiz-Verdú (2009) refer this as strategic fee setting.

I examine in this study whether there is cross sectional difference in fee choices and how fee choices vary by investor sophistication, as these issues are not sufficiently dealt with in the fee literature. Based on previous evidence, performance sensitive investors are expected to choose low fee funds since they are relatively more aware of the economics of investing in funds. Performance insensitive investors are expected to choose higher fee funds because they are invited through costly channels or aim to reduce search costs. My definition of investor sophistication and their fee choice are similar to Christoffersen & Musto (2002). According to their study, performance sensitive investors are prone to leave funds with poor track record. As a result, these funds are left with performance-insensitive investors. Therefore, it creates opportunity for bad managers to exploit the insensitivity by charging higher fees.

However, Christoffersen & Musto (2002) only cover fee choices. My study makes it convenient to compare not only fee choice, but also fund choice and timing abilities across investor sophistication. It is also of interest how these choices contribute to the bottom line of these investors. I find that the ability of fee choice is somewhat positively related to ability of fund choice but negatively related to timing ability. I offer explanation of these interaction in the discussion section. It also confirms previous findings that sophisticated investors have somewhat smarter fee choices, either to facilitate their timing decisions or keep the cost down.

2.1.3 Market Timing Abilities

While fee and abnormal returns constitute important parts of fund investments, these are only the financial side of the thing. In real world, investor move into and out of funds with significant frequency, as what has been observed on the fund flows. These cash flow amounts to billion US dollars per month. According to stylized view on active investment, the cash flows may reflect 1. decisions of investors to allocate assets across different asset classes based on expected yield on the asset class (asset allocation) 2. Investors' reaction to assessed prospect of a specific fund with regard to the cross-section of peer funds (security selection) or 3. Investors' reaction to expected return on a specific fund (market timing, Andonov et al. 2012; Levy & Lieberman 2016). As long as investors alter their positions on fund investments during their horizon, the real return on their investment would most likely differ from buy-and-hold strategy, resulting to a timing effect.

The previous study on fund investor performance barely cover the timing effect. All of the studies I have referred to above (especially ones on fund selection ability) are based on an implicit but immensurable assumption: the assessed performance (oftentimes the risk adjusted return) is achievable only when investors do not alter the position on his investments. The observed portfolio balancing activities in mutual fund market render this assumption unrealistic. The use of fund returns to assess investor performance is thus questioned. When scholars derive some performance measure from fund returns, it is the performance of investment managers, not investors. It is crucial to distinguish the return earned by managers and the return earned by investors. As this study aim to provide a thorough examination on investor performance, I cover this issue by measuring the timing effect.

The timing effect is measured as the difference between buy-and-hold return and a dollar-weighted return calculated from fund flows. Thus, it is the actual loss from portfolio rebalance, or a measure of performance gap (the opportunity cost). This measure follow many market timing literature, for example Friesen & Sapp (2007). I have found that average investors loss much more from trading than the value created by active management. During the corresponding period, active equity funds generally yield four factor alphas ranging from -0.2% to 0.1% per month, while the performance gaps can be as large as 0.8% per month, although the results varies across samples. The magnitude of performance gap also dwarfs the fee they paid to managers. This suggest how detrimental trying to time the market may be to your wealth.

Since traditional finance has discovered the existence of time varying risk premium, time varying risks and time varying risk appetites, many argue that these discoveries justify active portfolio rebalance within or across asset classes. By engaging in active rebalance, investors enter the market when expected return is high and exit the market when expected return is low. Finely timed rebalance will optimize investment outcomes. Rational expectations ensure a representative investor foresee these opportunities and act as a perfect utility maximizer. However, my study depicts a grim picture. Mutual fund investors, mostly comprise of individual investors, do not seem to identify these investment opportunities correctly. They are better off adopting a buy-and-hold strategy.

My result on average timing abilities echoes a plethora of literature which have found bad market timing abilities of individual investors versus institutional investors, given that U.S mutual fund market is mostly participated by households. Barber & Odean (2000) examine a unique dataset containing complete individual investor transaction records. In their study, individuals that trade frequently underperform those trade infrequently by 7% annually. In additional, individual investors in average underperform benchmark index by nearly 1% per year. They argue these are the results from excessive trading, instead of liquidity needs, risk-based rebalancing and tax concerns. The arguments are later confirmed by Grinblatt & Keloharju (2009). Grinblatt & Keloharju (2000) study the Finnish market. Individual investors are characterized as impatient – they are eager to sell on positive realized return and buy after negative realized return, so that they fail to catch the momentum and yield lower than average return. Kaniel et al. (2008) and Griffin et al. (2003) offer similar evidences. Barber et al. (2009) document bad individual timing ability in Taiwan market, where overly aggressive orders cost individuals 3.8% annually. The portfolios individuals sell consistently outperform the portfolios sold. They also find that institutions reap the benefit from trading against individuals.

Mutual funds literature offer more evidences. There is concrete evidence of a positive correlation between mutual fund flows and contemporaneous or lagged market returns (Warther 1995; Remolona, Kleiman and Gruenstein 1997; Edwards and Zhang 1998; Fant 1999; Cha and Lee 2001; Goetzmann and Massa 2002; Alexakis *et al.* 2005; Oh and Parwada 2007; Cao, Chang and Wang 2008), suggesting that mutual fund investors chase market return; A positive correlation between mutual fund flows and fund performance (Ippolito 1992; Gruber 1996; Chevalier and Ellison 1997; Zheng 1999; Jain and Wu 2000; Lynch and Musto 2003; Ferreira *et al.* 2012; Berggrun and Lizarzaburu 2015), suggesting mutual fund investors chase fund return.

While these literature try to describe and explain the timing pattern of mutual fund investors, others direct measure their timing performance. Dollar weighted returns and flows are two convenient workhorses. Since the supply of mutual funds are fully elastic, flow reflect marginal demand from investors. Dollar weighted return utilize these dollar demands to weight returns during each periods as an approximation to timing performance. Nesbitt (1995) calculate dollar weighted returns using aggregated flows in US market during 1983-1994. Equity and bond fund investors are found to show consistent performance gaps. Friesen & Sapp (2007) expand their result by using fund level flows. They find that during 1991-2004, funds with different size, objective, or risk-adjusted performance show consistent performance gaps. In addition, investors in index funds show similar performance gaps as investors in non-index funds. In a later simulation test, they find that the reason behind bad timing performance may be overconfidence and return chasing. Bullard et al. (2008) extend findings of Friesen & Sapp (2007) by considering the effect of share classes. They find Class B, share class commonly rely on the recommendations of brokers, show the worst timing performance. They argue that these brokers may maximize marketing outcome by focusing on recent extreme returns instead of true prospects of the funds. Using similar methodology, Dichev & Yu (2011) observe a significant performance gap on hedge fund investors. The estimated gap range from 3% to 7% annually. Ciccotello et al. (2011) mentions the existence of a capacity effect in calculating dollar-weighted flows. After disentangling the capacity effect and timing effect, index funds are found to be affected by only timing effect and non-index funds are affected by both.

Please note that measure of timing ability takes many forms and the performance gap measure in this study is just a special case. Some argue that bad timing arises from investor sentiment. This is similar to our notion that bad timings are result of erroneous forecast of fund prospect. When mutual fund investors flood into high sentiment, or “glamour” funds, they face lower expected returns caused by reversal towards fundamental Baker & Wurgler (2006). The limits to arbitrage story of Shleifer & Vishny (1997) predicts that an investment whose fundamentals are easy to determine should suffer less from sentiment since arbitrage opportunities are clearer and there are less constraints on arbitrage. Although the fundamental of mutual funds are much more concrete than stocks and bonds (since fund managers report intrinsic per share portfolios values at a designated frequency), empirical evidences suggest sentiment play no less role in mutual fund transactions. Using questionnaires, Goetzmann & Peles (1997) detect a constant positive bias in the memory of mutual fund investors that may have caused performance persistence. Harless & Peterson (1998) provides similar evidences. Goetzmann et al. (2000) finds a strong behavioural factor extracted from the flows between equity funds and money market funds. The factor along explains 45% of cross-sectional dispersion in equity returns. It also offers additional explaining power on top of Fama and French three factors. They argue that the new factor may reflect mass sentiment towards equity premium. Goetzmann & Massa (2002) find similar factor in US daily equity fund flows and Brown et al. (2003) in Japanese daily fund flows. Indro (2004) find feedback loops between mutual fund flow and AAII sentiment index. A later investigation confirmed that the effect is independent from expectation of equity premium and macroeconomic fundamental. Frazzini & Lamont (2008) takes a portfolio holding approach. They calculate the percentage of mutual fund holding of CRSP common stocks due to incremental allocation of mutual fund flows. At a three-year horizon, stock returns are highly negatively related to incremental holdings and a long short strategy based on incremental holding deciles generate substantial abnormal returns. This suggest that investors timings are systematically wrong: they increase allocation to funds when valuation are high and decrease allocation when valuations are low. Ben-Rephael et al. (2012) construct a sentiment index from stock-bond migration. It is similar to Goetzmann et al. (2000). They find that the sentiment index is associated to excess market return which is reversed in the future. To further test whether it is a valid sentiment measure, they examine its effect on stock with characteristics which Baker & Wurgler (2006) proposed are most sentiment-prone. The result shows that small and glamour stocks are most connected with the sentiment index.

Some literature try to assign the observed flow-return relationship with rational explanation. For example, risk appetite (Jank 2012; Chalmers, Kaul and Phillips 2013), price pressure (Edelen 1999; Ben-Rephael, Kandel and Wohl 2011; Lou 2012; Vayanos and Woolley 2013) and tax (Bergstresser and Poterba 2002; Ivkovic and Weisbenner 2009). However, my study joins the abundant cases above showing that fund investors lose money, not make money in trading. Since the chapter focus on performance evaluation, I do not cover any predictive relationship nor invoke any debate between rationality and irrationality. The large performance gaps show that timing is a very important determinant in the realized return of investors, regardless of their sophistications. No matter what motivation is behind this systematical misallocation, the chapter show that deviation from a traditional buy-and-hold paradigm could be particularly jeopardizing for fund investments. A same view could be found on Bailey et al. (2011).

The chapter also contributes to the extant timing literature by discovering a cross-sectional dispersion in timing ability. Interestingly, sophisticated investors have a worse timing ability than unsophisticated investors, reflected in their mean performance gaps. This suggest investor sophistication in fund market is multi-dimensional. Gruber (1996) speaks of a dichotomy that sophisticated investor make decision on fund performance and unsophisticated or disadvantaged investors base investments on other factors. As a result, these sophisticated investors are able to optimize their financial performance. What I find shows that these performance-sensitive investors indeed earn high alpha, however they are penalized on below-par timing decisions. I offer explanations at the discussion section.

In addition, I also address an issue in past timing literature (Nesbitt 1995; Dichev 2007; Friesen and Sapp 2007; Bullard, Friesen and Sapp 2008; Dichev and Yu 2011) and propose improvements. The issue lies in the calculation of dollar weighted returns. The common practice to calculate dollar weighted return is to use some measure of investment flows and some measure of stock value at the start or end of a period. The investment flows could be fund flows (Friesen and Sapp 2007; Bullard, Friesen and Sapp 2008) or stock distributions (Dichev 2007). These investment flows are usually set to the highest available frequency. The stock variable is either Asset Under Management (Friesen and Sapp 2007) or market capitalization (Nesbitt 1995; Dichev 2007). For example, the performance gaps in Friesen & Sapp (2007) are calculated from monthly fund flows; the "distributions to investors" measure in Dichev (2007) are calculated from monthly aggregated market capitalizations and returns.

However, the calculation of dollar weighted return by these authors suffer from a caveat: by using the highest available flow frequency, they are calculating a return of a representative investor that trade in accordance with the specified frequency at exactly each period end. This is an overly strong assumption. Not every investor chooses to rebalance monthly. Statistics from Investment Company Institute suggest longer average holding period for fund investors. Sirri & Tufano (1998) add that implied average holding period could be as long as seven years, which justify their methodology of amortizing load fees over seven years. If investor make erroneous forecast of expected returns in every period in average, the estimated performance gap could be upward biased – it is not fair for investors who choose to stay in their funds or trade with smaller frequency.

Since I strive to evaluate performance for all investors, I take a more dynamic view: the dollar weighted return is function of both the magnitude and timing of cash flows. While successfully capture the magnitude of these cash flows, the performance gaps calculated by previous literature are static in terms of frequency, thus these are special cases. The solution in this chapter is to change the frequency of these cash flows to mimic timing performance of investors of various horizons. It is done through omitting periodic observations. I calculate new performance gaps using not only monthly fund flows, but also quarterly, semi-annually, annually and bi-annually. The results show the previous measures of performances gaps are truly upward biased. Average performance gaps decrease monotonically with frequency. At yearly rebalance, performance gaps are indifferent from zero. In other words, investors can simply choose to trade less to avoid wealth destruction. The result is a remarkable manifestation of market efficiency proposed by Fama (1991). They argue that private information is rare and costly to obtain. As a result, active investments would not outperform a simple buy-and-hold strategy for diversified portfolios.

More interestingly, through the dynamics of performance gaps, I observe a significant misalignment in performance improvement for each sophistication deciles. The chapter is the first to document these misalignments. The performance gaps for most sophisticated investors, decile 9 and 10, decrease faster than other investors when trading frequency is reduced. When trading frequency is set to annually or bi-annually, these two deciles even profit from timing – the performance gaps turn *negative*. Meanwhile, other deciles do not outperform buy and hold strategy by trading less under the same scenario. The performance gaps for deciles 1-8 are not significantly above zero with any frequencies. This suggest that sophisticated investors defined on fund selection ability do have some long-term timing ability, probably from betting on long term variation of economic risk premia. The result also joins studies on the optimum rebalance frequency when returns are predictable Barberis (2000); Almadi, Rapach and Suri (2014) by showing what rebalance frequency suit fund investors with certain degree of sophistication.

2.2 Methodology

As I intent to examine the investment performance for investors with different degree of sophistication, an appropriate proxy should be chosen to span the variation of sophistication.

Previous literature suggests multiple measures of sophistication. In one aspect, the channel in which investors choose to purchase funds may be correlated with their sophistication. Barber et al. (2005), Bergstresser et al. (2009) suggest that unsophisticated investors are more likely to choose broker-sold funds than direct-sold funds, since these investors are arguably less wealthy or financially knowledgeable. Chalmers and Reuters (2013) confirms that it is indeed the case. In addition, direct-sold funds are more economically efficient, since these funds generally charge less broker fee, loads and 12-b1 fees. Wealth is also a potential candidate. Previous evidence suggest that less wealthy investors are less competent in trading Barber and Odean (2000); influenced by disposition effect Bailey, Kumar and Ng (2011) and diversify insufficiently (Calvet, Campbell and Sodini 2006). A group of papers also use share classes to infer sophistication. Mutual funds typically divided shares into institutional and non-institutional share classes. Individual investors are not likely to afford the institutional class since it requires higher minimal investments. Guercio & Tkac (2002) finds that clients of pension funds, a typical category of institutional investors, do not flock to recent winners or tolerate poor performers like the mutual fund investors do. Barber & Odean (2012) documents less attention-driven buying behaviour of institution investors, since institutions derive considerable amount of resources into discovering valuable buying opportunities. Guercio & Tkac (2002), Barber et al. (2016) finds that institutional investors use more sophisticated measure to adjust for manager performance.

Although these measures are proven to span at least some variation in sophistication, I argue that they are less suitable for the topic in this study. Firstly, many of these measures are dichotomies. Funds are either broker-sold or direct-sold, and they are either institutional shares or non-institutional shares. There is hardly anything in between. Any test based on these dichotomies does not show the whole picture. In addition, these tests lack statistical power.

Secondly, measures based on investor characteristics are not easily obtain. Microeconomic proxies, such as investor wealth, education and marital status are highly source dependent. Due to the availability of the data, several papers have to use overlapped datasets, for example the Finnish dataset originated from Grinblatt & Keloharju (2000) and the Large Discount Brokerage dataset originated from Barber and Odean (2000). This sharing of datasets not only brings about data mining concerns, but also eliminated the possibility of replicability.

Therefore, it is crucial that an easily calculatable, universally available measure of fund investor sophistication be established. Out of these requirements, this study use the performance sensitivity of flows to proxy for sophistication. The underlying theory is fund investor rational learning, which assumes that fund investors infer the quality of managers from recent returns. The learning process creates some sensitivity of flows to performance. Ippolito (1992) pioneered that return of mutual funds are salient to investors since it can be viewed like the quality of a product. Gruber (1996) suggest two classes of investors – a sophisticated class which is performance sensitive, and a restricted class which is performance insensitive. Christoffersen & Musto (2002) shows the pricing mechanics of mutual funds. High fee funds, which not necessarily represent better (if not worse) funds, are able to maintain their price tag because they are facing a flat demand curve. Performance sensitive investors recognize the price tag and flee to economically competitive funds. Berk & Green (2004) depicts an equilibrium framework where performance sensitive flows compete for funds with best recent return. When diseconomy of scale is assumed, all funds will earn the same risk adjusted return in equilibrium. Huang et al. (2007) and Huang et al. (2012) not only confirms that performance is an important signal learned by investors, but also consolidates the rational learning story by discovering several parameters that alter this learning behaviour, such as participation cost, volatility of track record and fund age. Choi et al. (2016) shows that investors are not only sensitive to the performance of the fund they invest, but also the performance of the fund managed by the same manager. They also rule out the possibility of simple return chasing by using a placebo sample. Inspired by the rational learning story, Barber et al. (2016) use the sensitivity of flows to risk adjusted performance defined by several factor models to reveal the actual model used by investors; Berk & van Binsbergen (2016) are similar in spirit but they interpret the result as a test for true asset pricing model.

The sensitivity of flow to performance fits our objective of simplicity and availability, since only flow and track record are used in calculation. Mutual funds in most part of the world is legally required to disclose their sale, redemption and track records. In US, Investment Company Act of 1940 required that investment companies disclose this information in Form N-SAR and N-1. Sophistication can be easily proxied by the regression coefficient of flows on returns, interpreted as performance sensitivities, without regard to any specific information on individual investors. In this section, I introduce the calculation of flows and returns, and the associated measures for investor performance in several aspects.

2.2.1 Calculation of Flows

Fund flows are the primary instrument to observe investor behaviour. According to

Patel et al. (1994), the change in AUM are either due to net new money or appreciation/depreciation in capital stocks. In this spirit, the flow variable $\mathrm{FLOW_{i,t}}$ is defined as the net percentage change of AUM not due to capital appreciation/depreciation so that it reflects pure demand shocks from investors. Imagine a fund with an AUM of 100 million at the end of 2014. In the prospectus of the fund at the end of 2015, the fund reports a return of 10% during the year and an end-of-year AUM of 130 million. I can easily infer that the net inflow of the fund during the year is 130-100*(1+10%)=20 million. Thus 20% of increase in AUM are attributable from investors' net purchasing decision. I adopt the same calculations of percentage flows from several studies including Ippolito (1992) and Sirri & Tufano (1998).

Equation 1

$$\mathrm{FLOW_{i,t}} = \frac{AUM_{i,t} - AUM_{i,t-1}\left(\frac{NAV_{i,t}}{NAV_{i,t-1}}\right)}{AUM_{i,t-1}}$$

Equation 1 shows the calculation of flow variable. The term $AUM_{i,t-1}\left(\frac{NAV_{i,t}}{NAV_{i,t-1}}\right)$ captures the change in AUM due to return on the fund portfolio. The $\mathrm{AUM_{i,t-1}}$ in denominator normalizes the flows. Note that this measure of flows assume that all flows happen at the end of a periodIppolito (1992). This should not be a problem if I select other variables with the same frequency.

2.2.2 Calculation of Performance Gaps

I define the periodic return on fund assets as the simple percentage change on fund NAV,

Equation 2

$$\mathrm{Return}_{\mathrm{i,t}} = \frac{NAV_{i,t}}{NAV_{i,t-1}} - 1$$

It is a simple return earned by an investor if it purchases the fund from manager at time t-1, hold the fund from time t-1 to t and redeem at the ongoing NAV. For buy-and-hold return that is longer than one period, geometric mean return will be a proper measure, since it considers the reinvestment of gains from past periods. In this study, the geometric mean serves as a benchmark against active rebalancing. The geometric mean return of a fund is:

Equation 3

$$\mathrm{Return}^{g}_{\mathrm{i\ to\ i+k}} = \sqrt[k+1]{\prod_{i}^{i+k} \frac{NAV_{i,t+k}}{NAV_{i,t+k-1}}} - 1$$

The geometric mean of a fund has two meanings. It measures the average buy-and-hold return when investors start with some initial fund investment, hold the fund for k periods without any rebalance and withdraw the fund at the end of time t+k. It also measures the average return experienced by the fund manager during the period. Note that the arithmetic mean $\mathrm{E(Return_i)}$ does not consider the reinvestments so it is inappropriate as a benchmark.

It is highly unlikely that every investor will adopt this buy-and-hold strategy. Investors rebalancing their portfolio out of risk, tax or other rational concerns. It is also documented that individual investors show gamble behaviours and are inclined to time the market (Kumar 2009; Bailey, Kumar and Ng 2011). The activities of these marginal investors lead to the observed flows. If we assume that a representative investor invests some amount at the initial time and align all his future decisions to the observed flows, at the end of the period he will earn a dollar weighted return, or the IRR of this hypothetic cash flows. I follow Dichev (2007), Friesen & Sapp (2007), Dichev & Yu (2011) to define dollar weighted return of the fund flows as the Return^{d} that satisfy the following equation:

Equation 4

$$\mathrm{AUM}_{t-k-1} * \left(1+\mathrm{Return}_{i-k\text{ to }i}^{d}\right)^{k} + \sum_{i-k}^{k} \mathrm{NCF}_{t-k} * \left(1+\mathrm{Return}_{i-k\text{ to }i}^{d}\right)^{k-i} = \mathrm{AUM}_{t}$$

where

$$\mathrm{NCF}_{t} = AUM_{i,t} - AUM_{i,t-1}\left(\frac{NAV_{i,t}}{NAV_{i,t-1}}\right)$$

The LHS of the equation is a future value of a stream of cash flows, including the initial amount purchased and all the periodic net purchase and withdrawal of the fund. The Return^{d} is the real return for this representative investor, as compared to a geometric return. The gap between Return^{d} and geometric mean return is my measure of loss (gain) from timing.

The innovation in this study is it recognize the importance of frequency in calculating Return^{d}. From Equation 4, it is obvious that Return^{d} is a function of both the magnitude and frequency of periodic cash flows. The measure mimics a sequence of trading for a representative fund investor that *exactly* follow the actual fund flows in every period of length k. For k with a unit of one month, the hypothetical investor will trade every month with the magnitude and direction of the observed monthly flows. For k with unit 3, the investor will trade every quarter, omitting the flows in between quarter ends. For k with unit 12, the investors will only adjust his fund portfolio annually. A k with unit 0 is indifferent to a buy-and-hold strategy, resulting to $\mathrm{Return}^{d} = \mathrm{Return}^{g}$

In reality, not every investor will adopt a strict buy-and-hold strategy and earn Return^{g}, nor will they all adopt a strategy as active as to trade every month as the flows does and earn Return^{d}. The ongoing fund flow studies do a good job in capturing the magnitude of flows, however they fail to acknowledge the frequency issue. Every literature using Equation 4 to calculate dollar weighted returns use a monthly k, which is just a special case of many possible Return^{d}s. For instance, Friesen & Sapp (2007), Bullard et al. (2008), Ciccotello et al. (2011). As I focus on examining the performance of investors with various characteristics, the change in k imitate behaviours of market timers with different rebalancing frequencies.

Return^{d} and Return^{g} measures the dichotomy between buy-and-hold and active trading. The gap between two measures how active trading affect the wealth of active investors. Imaging a dumb investor that flow into a fund when beginning-of-period expected return is low and withdraw his money when beginning of period expected return is high, he will jeopardize his return on this strings of transactions by earning a Return^{d} lower than the buy-and-hold return, Return^{g}, and vice versa. I define a performance gap variable that reflect the loss (or gain) from the trading decisions for a representative investor in every fund as:

Equation 5

$$\mathrm{G}_{\mathrm{i,t-k\ to\ t}} = \text{Return}^{g}_{t-k\ to\ t} - \text{Return}^{d}_{t-k\ to\ t}$$

A positive G means investor loss from its trading decisions and a positive G means investor outperform the buy-and hold strategy. Note that when k is equal to sample length, the performance gap will be zero since it is equivalent to a buy and hold strategy. The performance gap inherits the parameter k from Return^{d}. Performance gaps with different ks corresponds traders with different rebalancing frequencies.

2.2.3 Performance Attribution Model

A model for fund returns has two purposes: risk adjustment and determining fund styles. The alphas from a pricing model measure the manager skills and fund selection skills of investors. In addition, the factor loadings reveal the undiversifiable risk exposure chosen by managers, namely the styles of funds.

I follow Carhart (1997) and Sapp & Tiwari (2004) to model the return of a fund using Fama French Three factors and a Momentum factor. Carhart (1997) shows that a four-factor model is superior to CAPM and Three Factor Model in explaining the cross-section of fund return. The inclusion of the momentum factor in risk adjustment is also justified by the finding of Sapp & Tiwari (2004) against Zheng (1999) that its omittance would result to false judgement that investors are able to pick funds with good future returns. Factor model is also commonly used by practitioners for risk adjustments. Companies such as BARRA, Mobius, Bloomberg and Wilshire all market software that performs sophisticated return attribution analysis that decomposes portfolio returns into exposure to various passive indices. The periodic return is modelled using a return generation process:

Equation 6

$$\mathrm{Return}_{i,t} - \mathrm{R}_f = a_i + \beta_{1,i}\mathrm{ExMkt}_t + \beta_{2,i}\mathrm{SMB}_t + \beta_{3,i}\mathrm{HML}_t + \beta_{4,i}\mathrm{UMD}_t + \epsilon_{i,t}$$

In this equation, excess return of a fund at time t is decomposed into the return from bearing systematic risks, a long-term average abnormal return α_i, and idiosyncratic risk, ϵ_i. ExMkt is the excess return on market portfolio. The regression is run at fund level with an observation as long as the length of sample period. Alpha is computed within each sample period. SMB is the mimicking return for size effect. HML is the mimicking return for value effect. HML is the mimicking return for momentum effect. The idiosyncratic risk component ϵ is assumed to be i.i.d.

At any time, t, I define a new variable called performance residual (Return^{e}) from the above equation,

Equation 7

$$\mathrm{Return}_i^e = \alpha_i + \epsilon_{i,t} + \mathrm{R}_f$$

,which is similar to the performance residual used by Ippolito (1992).

The Return_i^e is used as a proxy for manager generated return at time t while α_i measures the average superiority of the manager during a time period. The key assumption in this model is that Return_i^e and α_i is the deviation from equilibrium market pricing, or the "free launch" discovered by the managers using their skills. A higher Return_i^e and α_i is a signal that the manager is good and vice versa. If investors are able to pick funds with good managers *ex-ante*, we will observe a positive correlation between their trading activities and the alpha of the fund they hold *ex-post*.

In addition, the factor loadings β_1, β_2, β_3 and β_4 grant us additional information regarding the style of the funds. For example, funds with a higher β_1, β_2 mirrors the traditional notion of a "growth" fund. Funds with a higher β_4 will be categorized as a momentum strategy fund. The divergence of fund factor loadings is a result from the allocation preference of a fund. I assume that investors know the style of the funds and use the known style as a guidance for future cross-sectional dispersion in fund returns. I also ignore the time-varying portfolio weight issue proposed by Brown & Goetzmann (1997) and assume consistent fund style through sample period, since we only need some crude *ex-poet* categorization of fund styles.

Another caveat is that in reality, many funds would choose its own benchmark and strive to beat its own benchmark. The Exmkt, SMB, HML and UMD factors in this study are common risk factors for every portfolio in the market. Not every fund adjusts their return using these factors. Thus, the result of this study only indicates how a fund perform in terms of the broad market rather than its own benchmark. Nonetheless, the choice of a set of common risk factors mimic the performance of a fully diversified investor. It is a better linear combination of risk factors that represents the stochastic discount factor. It would be worthwhile to investigate how the fund choice of investors will affect their wealth as opposed to full diversification.

2.2.4 Flow-Residual Regression

I use the sensitivity of return to performance residual as a measure the sophistication of fund investors. Although the weak-form EMH predicts that there is no valuable information in past return of an asset to which one could trade to gain utility, Gruber (1996) and Ippolito (1992) shows that there is valuable information in fund performance residuals because they reflect long term manager ability. Other studies have found that manager ability is persistent, for instance Grinblatt & Titman (1992), Hendricks et al. (1993), Brown & Goetzmann (1995), Elton et al. (1996). The recent best performers tend to outperform peer funds while the recent worst performers seem to persistently underperform, at least in a short time period. These evidences also suggest that trading on performance residuals could be rational.

The return-performance relationship has a strong standing in past mutual fund studies. If we treat funds like commodities, the relationship between flow and performance is a bonding process by which consumers recognize product quality and act accordingly. Observing Equation 7, since $\alpha_{\mathrm{i}} = E(\mathrm{Return}_i^e - \mathrm{R_f})$, the realizations of returns of a fund reveal the inherent skill of the managers, although the process takes may take several periods to be learned because return is noisy. Ippolito (1992) comments that vigilant consumers filter information regarding manager skills from these realizations and make investment decisions. Christoffersen & Musto (2002) include the flow-performance relationship in their argument. They try to solve the puzzle that the best performing funds in the industry charge less fees than worst performing funds. They show that the reason why best funds charge less is that they are faced with performance sensitive investors. These investors are highly aware of the financial aspect of their investments, inviting competitions into this niche. In contrast, the worst performers are faced with less performance sensitive investors since the sensitive investors would already have fled. This insensitivity creates economic rent for bad managers.

The flow-performance relationship can also be characterized as a Bayesian rational learning process of economic agents to update the belief regarding the prospect of his investment product. Berk & Green (2004) establish a model according to which a strategy of allocating to recent best performers is rational. Investment flows compete for good managers and attenuate the marginal investment yield of these funds. Levy & Lieberman (2016) show that whether a fund is of active or passive attribute is crucial in determining its flow-performance relationship. When the underlying objective of funds are categorized as either passive or active, active funds shows greater sensitivity of flow to performance. They argue that this is because investors who invest in active funds aim to achieve returns at least commensurate with index funds. The higher flow-performance sensitivity is a manifestation of information seeking.

A key assumption in using performance residuals is that investors are actively conducting risk adjustments using latent factor like the Fama French factors. These will happen only on investors groups that are sophisticated enough. Unsophisticated investors are less likely to recognize these factors as they are documented to chase recent return blindly.

The points above justify the usage of flow-residual sensitivity as a proxy of sophistication in mutual fund market. To illustrate how this proxy works, let's imagine a mutual fund industry with no abnormal return in general, however, the cross-sectional variation in managerial ability results to cross-sectional variation in abnormal returns. Good managers are in general producing positive abnormal return, the long-term average of their performance residuals, at the expense of bad managers. In this scenario, active investment is a zero sum game before cost and a negative sum game after cost. Sharpe (1991) calls it the arithmetic of active investments.

A sophisticated investor who is engaged in a consistent strategy by purchasing funds with positive performance residuals and dump funds with negative performance residuals is able to outperform peer investors (the market) since they make the right pick in average. The more sensitive they are to the performance residuals, the more gain they will be awarded. An investor who do not trade on these signals will be awarded the market return, since their choices of funds are independent to the quality of these funds. An investor that trade opposite to the performance residuals will be punished to earn an inferior return, since they pick exactly the worse funds in average. As long as alpha is a valid measure of fund quality, the flow-residual sensitivity is positively correlated to the sophistication of investors. My perception of the relationship between sophistication and flow-return sensitivity is similar to Christoffersen & Musto (2002), who notes that "one could simply assume that the smart money is the active money, in which case the investors who remain in a fund of any type after more attrition are the relatively less performance-sensitive ones".

I run a flow-residual OLS regression to model the relationship between flows and performance residuals.

Equation 8

$$\mathrm{Flow}_{\mathrm{i,t}} = c_i \; + \gamma_{\mathrm{i,1}}\mathrm{Flow}_{\mathrm{i,t-1}} + \gamma_{\mathrm{i,2}}\mathrm{Return}^{e}_{\mathrm{i,t}} + \gamma_{\mathrm{i,3}}\mathrm{Return}^{e}_{\mathrm{i,t-1}} + \xi_{i,t}$$

$\mathrm{Return}^{e}_{\mathrm{i,t}}$ is defined as in Equation 7. The parsimonious model aims to capture the flow-residual sensitivity by loadings. The contemporary flow-residual sensitivity is γ_2 in the above equation. The lagged flow and lagged returns are to control for autocorrelation in flows and any other persistence from lagged return. Similar model can be found in Ippolito (1992); Patel et al. (1994); Warther (1995); Fant (1999); Berk and van Binsbergen (2016); Barber, Huang and Odean (2016).

Higher absolute value of γ_2 is interpreted as higher propensity to trade for or against the contemporaneous performance residuals. The sign of γ_2 decide whether an investor is a momentum trader or a contrarian trader, and the magnitude of γ_2 capture his aggressiveness. For example, an investor with a large positive γ_2 means in average he believes that there is a momentum in recent fund return and he trade aggressively in the same direction. A smaller absolute value of γ_2 means the investors are indifferent to recent return as in average he adopts a buy-and-hold strategy. The magnitude of the γ_2 model investors' aggressiveness and the sign of the γ_2 measures the direction of their transaction. The higher the magnitude of γ_2 for an investor is, the higher ability he should have to identify a good manager.

Since the flow data of funds are aggregated, I could not possibly obtain the flows for each investor. Thus γ_2 should be interpreted as an average measure of investor sophistication for a fund. An aggregated flow-residual sensitivity only predicts that when a fund has its flows positively correlated with its own performance residuals, it should have been favored by relatively sophisticated investor groups and as a result, produce higher risk adjusted returns. It does not mean that these funds are not invested by unsophisticated investors at all. Every fund can be invested by any investors. The γ_2 tells us whether a fund is *in average* favored by sophisticated or unsophisticated investors. A similar explanation is offered by Christoffersen & Musto (2002). They argue that the reason why the worst funds can survive in the market is because performance sensitive investors has already migrated to better funds. The performance insensitive investors remain in those funds and continue to bear with the inferior managers. γ_3 is not selected because Edelen & Warner (2001) and Ben-Rephael et al. (2011) document return chasing behaviours in daily frequency. In their studies, the flows are strongly related to returns on the same day. Any effect of return on past flows are reversed within a week. The monthly frequency in this study suggest that the relationship of flow and past return is second order. The concurrent flow-return relationship should be strongest and most informative. In a robust check, the usage of lagged coefficient γ_3 do not qualitatively change the result.

2.2.5 Timing and Fee Adjusted Abnormal Return

I measure investor performance with regards to alpha, fees and timing. Traditional equilibrium asset pricing model posits that the expected return of an asset is determined solely by its covariance with a set of systematic risks faced by investors. Out of this spirit, common method of evaluating the performance of mutual fund investors is to examine their risk adjusted return on their fund holdings, namely the alphas from a regression of fund return on several risk factors. The alphas are interpreted as long term average idiosyncratic component of manager generated return, or the abnormal return earned by investors.

Fees and timing costs do not enter into the risk-based model, since two common assumptions in this model is that market is frictionless, and investors are fully rational. Thus, it is paramount to note that the actual risk adjusted return of fund investors cannot be measured solely as the alpha of the portfolio of fund they choose. These alphas are earned by either fund managers or strictly buy and hold investors, before fee. In reality, investors often pay a hefty fee for remaining in a fund. These fees are the gain for managers and the loss for investors. The sample expense ratio in my study shows a maximum of 7% fees charged by managers per year, with the mean around 1.2%. The fees reflect either the cost of information discovery (Sirri and Tufano 1998; Huang, Wei and Yan 2007) or transaction cost (Carhart 1997), which are absent from a frictionless market assumption.

Timing decisions are also a potential drag on performance since mutual investors are documented to enter and exit the market in wrong times (Braverman, Kandel and Wohl 2005; Frazzini and Lamont 2008; Akbas *et al.* 2015). The reduction in wealth by wrong timing is a substantial opportunity cost since investors could have adopted a simple buy-and-hold strategy. Current explanations on why investors trade more frequently is unsettled. Behavioural campaign argues that psychological biases like overconfidence (Barber and Odean 2000; Grinblatt and Keloharju 2009), gambling (Kumar 2009; Bailey, Kumar and Ng 2011) or heuristic bias (Barber and Odean 1999; Friesen and Sapp 2007) are behind the excessive volume. Rational campaign maintain that rational motivation like tax (Bergstresser and Poterba 2002; Bailey, Kumar and Ng 2011), risk appetite (Jank 2012) or seasonal asset allocation (Kamstra *et al.* 2017) can explain these activities. However, this study is descriptive rather than normative. Whether the former or the latter holds, empirical result tells us that these actions by mutual fund investors cause their real performance to deviate from risk adjusted returns, rendering the alpha measure inadequate. Thus, we need a more comprehensive measure of investor performance by taking into account the transaction cost (fund fees) and timing costs.

I define the timing adjusted abnormal return (TAAR) as the alpha deducted by performance gap during some period:

Equation 9

$$\mathrm{TAAR_i} = \mathrm{Alpha_i} - \mathrm{Gap_i}$$

The TAAR is the real risk adjusted return by taking into account the loss (gain) from fund rebalancing. As long as investors trade, the performance gap will most likely deviate from zero. Success market timers will do better than their fund managers and they will earn more risk adjusted returns than the fund portfolio. Unsuccessful market timers will see a gap that eat into their alpha.

I also define the timing and fee adjusted abnormal return (TFAAR) as the TAAR after fees. As the units of the alpha and performance gap are monthly, total expense ratio is divided by 12 to mimic the carrying cost of holding the fund.

Equation 10

$$\mathrm{TFAAR_i} = Alpha_i - Gap_i - \frac{TER}{12}$$

The Alpha-TER/12 component in Equation 10 is similar to the "net alpha" measure used by several mutual fund studies (for instance Carhart 1997; Wermers (2000); Kosowski et al. 2006) to evaluate manager skills. This measure is in contrast to "gross alpha", a before fee measure. Fama & French (2010) call the net alpha "equilibrium accounting". I do not step into the debate on whether manager skills should be measured before or after fees, since the perspective is from investors – fees are what they have actually paid, thus fees should be deducted from their return. The TER/12 measure of carry cost follow the one from Fama & French (2010).

2.3 Data

2.3.1 Fund Data

Mutual fund data from this study is sourced from Datastream, which provide tracking records and Asset Under Management (AUM) for US mutual funds in monthly frequency. My sample contains record of all equity funds from December 1994 to December 2015. The database is not survivalship-bias free since Datastream drop a fund from the database once it is liquidated or merged. I check our sample AUM against the statistics from Investment Company Institute, a canonical purveyor of aggregated mutual fund data in US. In each month, ICI report the aggregated AUM for mutual funds registered in US. Table 2-1 summarize the total AUM in sample as a percentage of its ICI counterpart. The sample coverage is gradually improving. In the 1990s, nearly 30 percent of fund AUM vanished in my sample due to the discardment of Datastream. The 2000s saw a drastic improvement in coverage. During the first five years, the coverage goes from 70% to 90%. The coverage in 2010-2015 is nearly or equal to 100%, suggesting data for virtually every equity fund in US during this period is available. Nonetheless, a significant amount of capital stocks is captured in this sample. The equity mutual funds grow by 8 folds from 1 trillion to 8.15 trillion. The ICI Factbook suggest that these equity funds generally represent more than 50% of total mutual fund assets.

Table 2-1 Sample Coverage in Terms of Asset Under Management

Year	AUM of Equity Funds in sample	AUM as percentage of ICI statistics
	(1)	(2)
1994	0.58	69%
1995	0.87	70%
1996	1.21	70%
1997	1.70	72%
1998	2.17	73%
1999	2.94	73%
2000	2.87	73%
2001	2.58	76%
2002	2.10	80%
2003	2.99	82%
2004	3.65	84%
2005	4.26	87%
2006	5.22	90%
2007	5.87	92%
2008	3.32	91%
2009	4.55	93%
2010	5.19	93%
2011	4.94	95%
2012	5.67	96%
2013	7.56	97%
2014	8.25	99%
2015	8.15	100%

Unit: Trillion Dollars

Column (1) aggregates asset under management of sample equity funds in each year end. At each April, ICI, a leading research institution for US funds, also reports aggregate AUM for US equity fund of last year. Column (2) compares Column (1) with ICI figure for the same year, which serves as benchmark for full sample coverage. The percentage in Column (2) shows sample availability of AUM.

In addition, Datastream also label each fund by their Lipper Global Classifications, from which I identify their investment styles, geographical focus and asset classes. For example, a fund labelled "EquityNthAmericaSmMidCap" means the fund is an equity fund, invests a bulk of their assets in in North America market and focus exclusively on small and mid-cap stocks. A fund with "BondGlobalConvertibles" means the fund is a bond fund, invests in global convertible bond market. In this study, I focus specially in equity funds investing in domestic market since benchmark for other asset classes and other geographical regions are rather difficult to define or identify. For this purpose, I also drop all the funds with LGCs beginning with "Hedge" and "Alternative".

Other variables I obtain from Datastream are summarized below:

NAV: Actual Net Asset Value per share as reported by fund managers. It represents the per share portfolio value of a fund in a specific time. Datastream rebase the NAV for every funds if it acquires other funds.

AUM: Asset Under Management as reported by fund managers at end of every month. It is the total portfolio value of a fund.

FMC: The name of the fund management company.

ENAME: The full name for a fund.

TER: total expense ratio as reported in fund

TYPE: identify whether a fund is general mutual fund or pension fund.

2.3.2 Factor and Market Data

Monthly data for Fama and French four factors for US market are obtained from CRSP database. The four factors are Exmkt (the market factor), SMB (size factor), HML (value factor) and UMD (momentum factor). The calculation of the Exmkt, SMB and HML factors follow Fama and French (1993). The calculation of UMD factor follow Jegadeesh and

Titman (1993). It is a mimicking return for zero-investment one-year momentum portfolio. The four factors are popular instruments for risk adjustments both in the mutual fund industry or academic field.

I adopt the CRSP total market index for the market return. It is a comprehensive index including all stocks trading in Nasdaq, NYSE and AMEX. The portfolio aims to replicate the market portfolio.

2.3.3 Descriptive Analysis

Table 2-2 summarize the AUM, NAV and expense ratio (TER) of all domestic funds by year.

Table 2-2 Descriptive Statistics of Fund Characteristics by Year

Year	Number of Funds in Sample	AUM			NAV			TER		
		Mean	Stdev.	Median	Mean	Stdev	Median	Mean	Stdev.	Median
1994	730	661.0635	22.88847	153.1	17.52145	0.174705	14.25	1.085689	0.006389	1.01
1995	860	759.1632	25.51052	155.5	18.92514	0.181832	15.01	1.104717	0.00574	1.02
1996	1010	936.3941	28.60107	180	20.93634	0.19075	16.68	1.127231	0.005179	1.03
1997	1349	1032.928	29.52653	173.6	22.62125	0.192809	18.14	1.185075	0.004772	1.08
1998	1687	1071.035	29.81023	152.95	22.47843	0.181759	17.7	1.191361	0.004355	1.1
1999	2047	1152.88	31.81152	135.9	23.42192	0.181678	17.96	1.198803	0.003967	1.11
2000	2501	1173.706	29.51271	141.3	26.45353	0.532186	18.64	1.214954	0.003584	1.12
2001	3119	812.4159	19.32166	98.5	21.21104	0.42739	14.99	1.250474	0.003367	1.15
2002	3759	601.3473	13.7497	74.8	17.63002	0.316209	12.58	1.285317	0.003159	1.18
2003	4304	528.4119	11.69479	64.1	16.33048	0.159956	12.53	1.31418	0.002966	1.2
2004	4699	612.5312	12.83394	77.4	18.63786	0.082386	14.84	1.316053	0.002734	1.22
2005	5255	635.3783	12.62235	80.6	19.90252	0.081563	15.85	1.289925	0.002518	1.2
2006	5793	665.6838	12.4755	85.5	21.26404	0.080756	16.9	1.263009	0.002334	1.17
2007	6313	702.0647	12.67709	88.1	22.50201	0.081754	17.74	1.241207	0.002152	1.15
2008	6849	533.5616	9.667657	61.9	17.2612	0.06409	13.35	1.232206	0.002048	1.15
2009	7294	395.9763	6.962514	45.8	13.5737	0.047794	10.55	1.249451	0.002006	1.17
2010	7747	460.1325	7.63651	53.3	16.6779	0.053855	12.97	1.268331	0.001988	1.18
2011	8222	498.5195	7.833739	59.4	19.05515	0.059661	14.69	1.241807	0.001861	1.15
2012	8787	482.829	7.605846	54.5	19.4933	0.058099	15.05	1.228295	0.001782	1.15
2013	9360	552.3698	8.802092	61.2	22.83301	0.067243	17.71	1.216162	0.001722	1.13
2014	9871	626.9951	10.28572	66.1	25.02223	0.073675	19.34	1.190744	0.001633	1.1
2015	10367	630.8817	10.87486	62.2	24.10088	0.072207	18.68	1.176596	0.001578	1.1

The second column count equity funds which has at least an observation of AUM and NAV during the year. Asset Under Management is in millions. Total Expense Ratio is in percentage. Figures are as of each December.

Due to the potential effect of survivalship bias, I separate the sample into four periods for stability concern, with December 1994, December 2000, December 2005 and December 2015 as the breakpoints. Table 2-3 is the descriptive statistics of funds with different number of available observations during the last 5 years of the sample. For example, for all the 10,367 domestic equity funds during 2010-2015 (the full sample rows in Table 2-3), the mean AUM is 495 million and the mean expense ratio is 1.2%. For the 700 luck funds that dates back as long as December 1994, their average AUM is 2.4 billion and their average expense ratio is 1.02%. From Table 2-3, I observe an elimination mechanism in the fund market. Large and cheap funds survive while small and expensive funds cannot weather the force of market since the oldest funds seems to be a larger and cheaper subgroup among all funds. It may also be due to that the surviving funds earn enough time to grow big and managed to lower their price for service by economics of scale or competitive advantage. Nonetheless, even the 700 surviving funds provide us with enough dispersion in AUM and expense ratio as other funds. Thus, I can still get a usable cross-section by choosing these funds with corresponding time periods.

Table 2-3 Descriptive Statistics for Asset Under Management and Expense Ratio

	Earliest Available Year (as of Dec)	Number of Funds Survived	Mean	Std. Dev.	Min	Max
AUM	2015	10367	495.50	2746.89	0.10	90037.87
	2010	7544	620.88	3108.60	0.10	90037.87
	2005	4906	812.03	3749.60	0.10	90037.87
	2000	2263	1244.61	4951.21	0.12	90037.87
	1994	700	2439.79	7411.53	1.46	90037.87
Expense Ratio	2015	9448	1.20	0.53	0.00	7.00
	2010	7264	1.22	0.52	0.00	5.63
	2005	4719	1.22	0.54	0.00	5.63
	2000	2260	1.17	0.55	0.00	5.63
	1994	700	1.02	0.47	0.00	4.62

The table summarize survivalship of funds during each sample period. The Number of Funds Survived counts the number of funds that survived during the Earliest Available Year, which correspond to our sample break points, to December 2015. For example, the row “2010” counts funds with at least 60 observations. The row “2005” counts funds with at least 120 observations.

Table 2-4 is the descriptive statistics of fund flows and fund return by year. Flows in this study are trimmed at 1% level to avoid influence of extreme value. The mutual fund industry has seen an inflow in every year in the sample. The monthly inflow during the first 10 years amounts to 2-3% monthly, suggesting a burgeoning growth of fund assets. The speed of the inflow is decreasing by time. Meanwhile, fund returns match the anecdotal histories of stock market crash and rally. The negative returns during 2001, 2002 and 2008 are synchronous with the dot-com bubble and the 2008 financial crisis.

Table 2-4 Equal Weighted Mean Fund Flow and Fund Returns

Year	Percentage Flow		Fund Return	
	Mean	Stdv.	Mean	Stdv.
1994	0.028	0.059	-0.003	0.035
1995	0.031	0.06	0.02	0.033
1996	0.034	0.061	0.012	0.043
1997	0.036	0.066	0.014	0.054
1998	0.028	0.061	0.01	0.074
1999	0.025	0.065	0.019	0.056
2000	0.028	0.066	0.003	0.075
2001	0.025	0.063	-0.005	0.07
2002	0.021	0.062	-0.017	0.061
2003	0.024	0.062	0.026	0.038
2004	0.021	0.056	0.012	0.034
2005	0.017	0.055	0.007	0.033
2006	0.015	0.054	0.011	0.031
2007	0.015	0.056	0.005	0.035
2008	0.009	0.055	-0.037	0.076
2009	0.006	0.052	0.026	0.069
2010	0.006	0.051	0.016	0.058
2011	0.006	0.048	-0.001	0.055
2012	0.002	0.044	0.012	0.036
2013	0.007	0.046	0.023	0.03
2014	0.006	0.045	0.008	0.033
2015	0.004	0.044	-0.001	0.041
Sample	0.012	0.054	0.007	0.052

The table show arithemtric mean and standard deviation of flows and returns for all equity funds in sample. Caluculatio of flows follows Equation 1. To avoid influence of extreme values, flows are trimmed at 1% level. Calculation of fund returns follows Equation 3.

Figure 2-1 illustrate the time series of mean fund flows. The solid line is equal weighted flow while the dotted line is a value weighted flow using Asset Under Management. A clear pattern is that before the 2008 crisis, small funds has seen more inflows than large funds since the level of equal weighted flow is consistently higher than the value weighted flow. The flow of smaller funds is also more volatile, reflecting higher propensity to trade for investors of small funds. Another intriguing phenomenon is the spikes in December. The pattern match the findings of Kamstra et al. (2012) that mutual fund investors show seasonal asset allocation behaviour. They tend to leave equity funds during the autumn and re-enter the fund market at the beginning of the year. The seasonal allocation in this case is driven by large funds, since AUM weighted flows has almost the same end of year spikes as equal weighted flows.

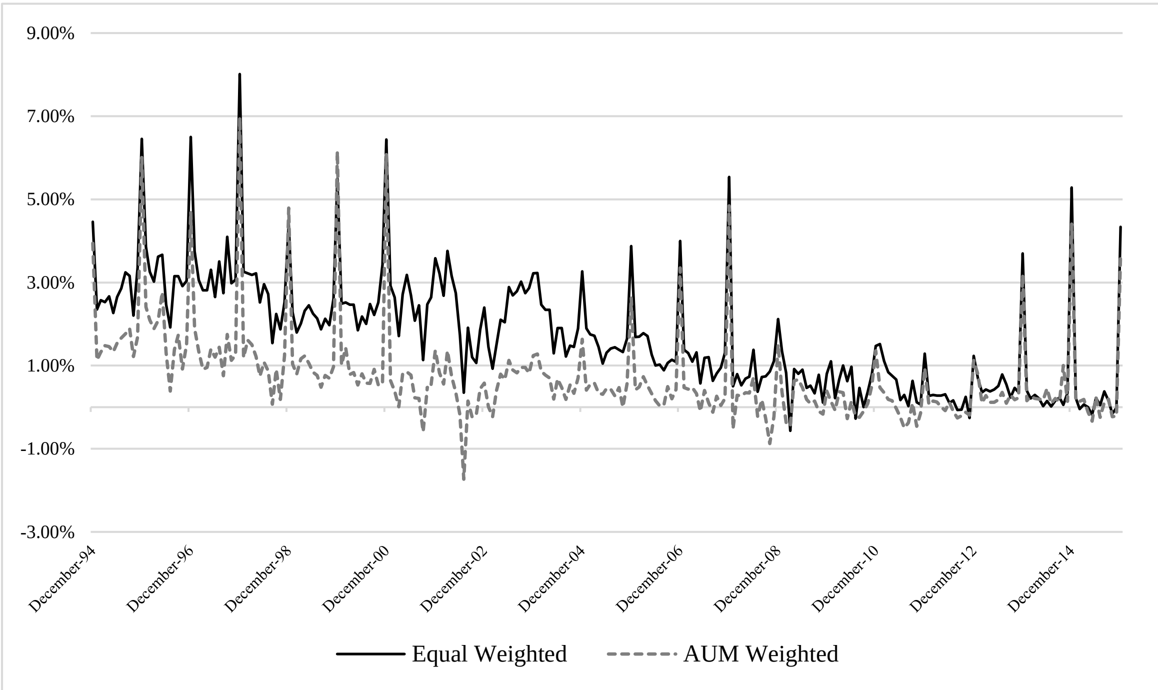


Figure 2-1 Mean Monthly Flow of US Equity Funds, 1994-2015

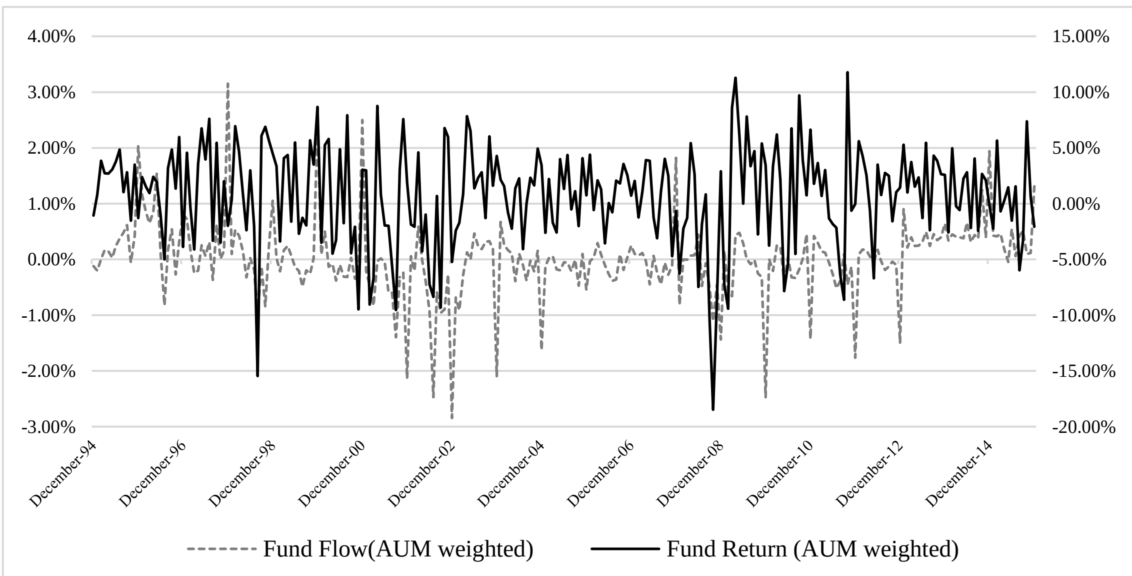


Figure 2-2 AUM Weighted Monthly Return vs Flow of US Equity Funds, 1994-2015

In Figure 2-2, I plot the de-seasoned and de-trended flow against monthly mean return of funds. To de-season and de-trend the flows, I regress the flow on time and a December dummy. The flow and return series are value weighted. I can see that the flows and returns are generally correlated contemporaneously. Higher fund returns are associated with higher inflows and lower returns are associated with an immediate outflow. It is either due to information in returns are absorbed by flows or there is a common factor driven both flows and returns. There is also a fairly amount of return chasing behaviour. Flows are somewhat related to the returns in the immediate past month. A check of the statistics shows that the correlation between flows and contemporaneous returns are 0.32, and the correlation between flows and past returns are 0.11. The magnitude of the correlation is similar to the findings of Warther (1995), Sirri & Tufano (1998) and Ben-Rephael et al. (2011). This also justify the use of contemporaneous sensitivity.

Table 2-5 summarize the contemporaneous flow-residual sensitivity, $\gamma 2$ by fund Lipper Global Classification, for sample period 2010-2015. The sample mean sensitivity is -0.031, which means investors are in average mildly contrarian to manager generated returns. The negative sensitivities are driven by the biggest three fund categories. All the sector funds except consumer staples have positive flow-residual sensitivities. Investors of financial and telecom services funds are particularly sensitive to return residuals, with sensitivities of 0.578 and 0.706 respectively.

According to Datastream, a fund with more than 60% of assets investing in foreign markets is categorized as foreign fund. Although I do not choose foreign funds in my analysis, I have included them in Panel (B). Mean sensitivity of foreign funds is also negative during 2010-2015, with the magnitude similar to domestic funds.

Table 2-6 summarize the risk adjusted returns of funds in each sample period. The alphas are taken from a fund level time-series regression as Equation (6). Equity funds are generating positive alpha for all sample periods except for 2010-201, when they are outperformed by passive benchmarks as much as 0.143% per year. During 1994-2000, the 700 sample funds beat the market by 0.245% per month, or 2.94% per year. This is either due to survivalship bias discussed by Rohleder et al. (2011) or diseconomy of scale discussed by Berk & Green (2004). By the former explanation, fund with bad managers or bad strategies gradually lose market and is eliminated. Lynch & Musto (2003) offers a thorough analysis. The latter explanation assumes that only mildly sized funds can generate alpha. As the fund grows, it experiences significant diseconomy of scale that reduce its marginal gain

Table 2-5 Mean Return-Residual Sensitivities by Lipper Global Classification, 2010-2015

LGC		$\gamma 2$	
(A)			
	Mean	Stdev	Median
EquityNorthAmeria	-0.079	1.283	-0.046
EquityNthAmericaSmMidCap	-0.058	1.295	-0.038
EquitySectorConsDiscretionary	-0.047	2.919	0
EquitySectorConsStaples	0.038	0.748	0.144
EquitySectorEnergy	0.052	0.282	0.04
EquitySectorFinancial	0.492	2.236	0.202
EquitySectorGoldPrecMetals	0.054	0.104	0.039
EquitySectorHealthcare	0.255	0.445	0.179
EquitySectorIndustrials	0.578	1.211	0.446
EquitySectorInformationTech	0.236	0.619	0.13
EquitySectorMaterials	0.023	0.316	0.044
EquitySectorRealEstGlobal	0.009	0.286	0.029
EquitySectorRealEstNAm	0.129	0.573	0.064
EquitySectorTelecomSrvcs	0.706	3.493	0.136
EquitySectorUtilities	0.244	0.482	0.112
EquityUSIncome	0.032	0.683	0.018
Mean Domestic	-0.031	1.234	-0.009
(B)			
EquityAsiaPacific	-0.014	0.41	0.021
EquityAsiaPacificExJapan	-0.082	0.402	0.014
EquityEmergingMktsGlobal	-0.031	0.256	-0.026
EquityEmergingMktsLatAm	-0.002	0.191	0.013
EquityEurope	0.106	0.538	0.129
EquityGlobal	-0.124	0.473	-0.09
EquityGlobalexUS	-0.069	0.346	-0.039
EquityGlobalexUSSmMidCap	-0.025	0.319	0.006
EquityGlobalIncome	-0.243	0.66	-0.081
EquityGlobalSmMidCap	-0.056	0.428	0.026
EquityGreaterChina	0.103	0.215	0.088
EquityIndia	0.101	0.106	0.089
EquityJapan	0.154	0.3	0.158
Mean Foreign	-0.068	0.387	-0.033

$\gamma 2$ is the coefficient on contemporaneous fund return in Equation (3). Column (A) includes domestic equity funds, which are used in this study. Column (B), serves as comparison, includes foreign funds, which are excluded in this study. The definition of Domestic or Foreign are according to LGC.

Table 2-6 Carhart Four Factor Alpha by Lipper Global Classification

LGC	Alpha(2010-2015)		Alpha(2005-2010)		Alpha(2000-2005)		Alpha(1994-2000)		Alpha(1994-2015)	
	Mean	Stdev.	Mean	Stdev.	Mean	Stdev.	Mean	Stdev.	Mean	Stdev.
EquityNorthAmeria	**-0.116**	0.157	**0.145**	0.185	**0.061**	0.208	**0.287**	0.357	**0.124**	0.145
EquityNthAmericaSmMidCap	**-0.132**	0.196	**0.151**	0.230	-0.005	0.335	**0.124**	0.395	**0.083**	0.179
EquitySectorConsDisc	-0.038	0.406	**0.196**	0.156	0.041	0.279	0.192	0.233	**0.241**	0.133
EquitySectorConsStaples	-0.019	0.211	0.407	0.600	**0.248**	0.188	-0.275	0.762	0.260	0.201
EquitySectorEnergy	**-1.217**	0.450	**0.880**	0.323	**0.716**	0.322	**0.266**	0.396	-0.065	0.151
EquitySectorFinancial	-0.068	0.394	**-0.318**	0.477	**0.254**	0.173	0.017	0.262	**0.160**	0.186
EquitySectorGoldPrecMetals	**-1.659**	0.468	**2.267**	0.359	**1.163**	0.346	**-1.154**	0.757	-0.047	0.232
EquitySectorHealthcare	**0.708**	0.321	**0.293**	0.191	**0.321**	0.298	**0.971**	0.810	**0.487**	0.192
EquitySectorIndustrials	-0.092	0.506	**0.444**	0.206	-0.009	0.256	0.231	0.556	0.090	0.306
EquitySectorInformationTech	**-0.091**	0.289	**0.354**	0.246	0.029	0.409	**0.996**	0.468	**0.308**	0.201
EquitySectorMaterials	**-0.648**	0.385	**0.956**	0.274	**0.846**	0.196	-0.152	0.486	**0.366**	0.151
EquitySectorRealEstGlobal	**-0.334**	0.201	**0.099**	0.278	**0.958**	0.177	-0.075	0.710	0.025	0.222
EquitySectorRealEstNAm	0.015	0.268	**0.102**	0.253	**0.847**	0.224	**0.322**	0.176	**0.367**	0.078
EquitySectorTelecomSrvcs	**-0.169**	0.382	**0.225**	0.329	0.246	0.620	**0.634**	0.336	0.254	0.271
EquitySectorUtilities	-0.073	0.309	**0.566**	0.220	-0.060	0.192	**0.485**	0.225	**0.182**	0.117
EquityUSIncome	**-0.133**	0.158	**0.238**	0.170	**0.065**	0.196	**0.336**	0.251	**0.154**	0.115
Pension Funds	**-0.104**	0.239	**0.189**	0.231	**0.089**	0.284	**0.425**	0.303	**0.181**	0.117
Mutual Funds	**-0.153**	0.324	**0.188**	0.326	**0.101**	0.350	**0.201**	0.473	**0.109**	0.179
Mean Domestic	**-0.143**	0.310	**0.188**	0.309	**0.098**	0.337	**0.245**	0.453	**0.123**	0.171

Alphas are regression constant from time series regression of fund returns on four factors, including Exmkt, SMB, HML and UMD. The definition of pension fund and mutual funds are reported by Datastream via variable REMK. The sample 2010-2015 contains all domestic equity funds with observations larger or equal to 60. The sample 2005-2010 contains all domestic equity funds with observations larger or equal to 120. The sample 2000-2005 contains all domestic equity funds with observations larger or equal to 180. The sample 1994-2000 contains all domestic equity funds with observations larger or equal to 250. Alphas in bold indicate statistically significant at 95% level.

Table 2-7 Carhart Four Factor Loadings by Lipper Global Classification, 2010-2015

LGC	$Beta_1$		$Beta_2$		$Beta_3$		$Beta_4$	
	Mean	Stdev.	Mean	Stdev.	Mean	Stdev.	Mean	Stdev.
EquityNorthAmeria	1.007	0.093	0.004	0.150	-0.081	0.255	-0.008	0.066
EquityNthAmericaSmMidCap	1.004	0.104	0.606	0.239	0.019	0.249	0.019	0.091
EquitySectorConsDisc	0.984	0.238	0.057	0.308	-0.253	0.175	0.037	0.140
EquitySectorConsStaples	0.899	0.128	-0.244	0.308	-0.094	0.141	0.124	0.163
EquitySectorEnergy	1.166	0.179	0.239	0.184	0.556	0.273	-0.438	0.166
EquitySectorFinancial	1.049	0.199	0.209	0.209	0.322	0.149	-0.036	0.160
EquitySectorGoldPrecMetals	0.294	0.140	0.515	0.375	-0.310	0.282	-0.843	0.159
EquitySectorHealthcare	0.837	0.065	0.351	0.272	-0.647	0.317	0.117	0.089
EquitySectorIndustrials	1.065	0.148	0.256	0.124	0.004	0.247	-0.010	0.095
EquitySectorInformationTech	1.054	0.123	0.100	0.208	-0.556	0.225	-0.192	0.148
EquitySectorMaterials	1.177	0.105	0.299	0.122	-0.044	0.173	-0.336	0.148
EquitySectorRealEstGlobal	0.876	0.107	-0.144	0.093	-0.016	0.083	0.050	0.114
EquitySectorRealEstNAm	0.793	0.137	-0.072	0.114	-0.078	0.129	0.287	0.098
EquitySectorTelecomSrvcs	0.849	0.084	-0.277	0.186	-0.120	0.226	-0.057	0.279
EquitySectorUtilities	0.640	0.150	-0.196	0.149	0.291	0.094	0.221	0.160
EquityUSIncome	0.923	0.107	-0.113	0.109	0.147	0.102	0.017	0.074
Mean Domestic	0.988	0.136	0.196	0.343	-0.040	0.290	-0.006	0.145

This table checks fund factor loadings against actual LGC reported by Lipper/Datastream. The comparison reveal whether reasonable measure of fund styles are obtained. Beta 1, Beta 2, Beta 3, and Beta 4, are factor loading on excess market return, SMB, HML and UMD mimicking returns respectively. The factor loadings measure degree of exposure to systematic risk factors, thus serves as quantitative measures for fund style. For better benchmarking, only equity funds defined as domestic oriented are selected. The last row aggregates all domestic equity funds.

from investments. In equilibrium, the fund industry will earn an average market return Berk and Green (2004). I also compare the performance of pension funds and mutual funds. The pension funds outperform pension funds in all but 2000-2015. During the 1994-2000 sample, pension funds offer as much as twice risk adjusted returns than mutual funds.

Table 2-7 match the Lipper Global Classification with the factor loadings I obtain in Equation (6). The sample period is 2010-2015 since Datastream only offer the latest LGC. Observing the mean factor loadings, we can see that the average mutual funds are inclined to hold small, value and contrarian stocks. The biggest category, EquityNorthAmerica, are fairly neutral to risk factors. Meanwhile, EquityNthAmericaSmMidCap has a much larger loading on SMB factors. They indeed hold smaller stocks as it has claimed. EquityUSIncome, as its name suggests, generally hold small beta, large and growth stocks. Fund investing in the gold and precious metal sector has the smallest beta as stocks in these sectors are less correlated to the market. The matching between betas and LGCs confirms that my style scheme is effective in categorizing funds.

Table 2-8 shows the performance gaps as calculated by Equation (5). The dollar weighted returns are internal rate of returns of monthly cash flows during each sample periods, with the starting and terminating cash flows being the AUM of the fund. Note that not every fund has a proper dollar weighted returns since internal rate of return suffer from multiple solution problem. To conform to the limited liability constraint, my algorithm filters out all the roots that is smaller than -100%. In addition, the searching stops when it finds a root which is closest to the geometric return. The procedure left me with 96% of funds with a proper dollar weighted return.

Table 2-8 Equal Weighted Mean Performance Gap of Domestic Equity Funds by LGC and fund TYPE

LGC	Gap(2010-2015)		Gap(2005-2010)		Gap(2000-2005)		Gap(1994-2000)		Gap(1994-2015)	
	Mean	Stdev.	Mean	Stdev.	Mean	Stdev.	Mean	Stdev.	Mean	Stdev.
EquityNorthAmeria	**0.91%**	0.002	**0.31%**	0.002	**0.35%**	0.003	**1.08%**	0.004	**0.55%**	0.002
EquityNthAmericaSmMidCap	**0.84%**	0.002	**0.45%**	0.002	**0.68%**	0.004	**0.82%**	0.004	**0.59%**	0.002
EquitySectorConsDisc	**1.11%**	0.002	**0.53%**	0.004	**0.39%**	0.004	**0.73%**	0.002	0.63%	0.002
EquitySectorConsStaples	**0.93%**	0.002	**0.52%**	0.001	**1.13%**	0.006	**0.31%**	0.003	**-0.16%**	0.003
EquitySectorEnergy	**0.32%**	0.003	**0.73%**	0.004	**1.48%**	0.005	**0.65%**	0.003	**0.47%**	0.002
EquitySectorFinancial	**0.87%**	0.003	**0.30%**	0.003	**0.57%**	0.003	**1.25%**	0.002	**0.56%**	0.001
EquitySectorGoldPrecMetals	N/A	N/A	**1.74%**	0.003	**2.31%**	0.003	N/A	N/A	N/A	N/A
EquitySectorHealthcare	**1.58%**	0.003	**0.38%**	0.002	**0.43%**	0.003	**1.29%**	0.007	**0.81%**	0.002
EquitySectorIndustrials	**0.87%**	0.003	**0.58%**	0.002	**0.78%**	0.001	**1.06%**	0.007	**0.59%**	0.001
EquitySectorInformationTech	**0.96%**	0.003	**0.65%**	0.003	0.06%	0.001	**1.21%**	0.005	**0.42%**	0.003
EquitySectorMaterials	**0.58%**	0.003	**0.96%**	0.004	**0.97%**	0.006	**0.76%**	0.001	**0.93%**	0.001
EquitySectorRealEstGlobal	**0.53%**	0.002	**0.26%**	0.002	**1.48%**	0.003	0.53%	0.006	**0.68%**	0.003
EquitySectorRealEstNAm	**0.91%**	0.003	**0.30%**	0.002	**1.43%**	0.002	**0.80%**	0.002	**0.78%**	0.002
EquitySectorTelecomSrvcs	**0.70%**	0.003	**0.46%**	0.004	**0.43%**	0.002	**1.18%**	0.006	0.81%	0.006
EquitySectorUtilities	**0.62%**	0.002	**0.45%**	0.002	**0.29%**	0.002	**1.09%**	0.002	**0.55%**	0.001
EquityUSIncome	**0.76%**	0.002	**0.29%**	0.001	**0.35%**	0.002	**0.96%**	0.003	**0.55%**	0.001
Pension Funds	**0.93%**	0.002	**0.39%**	0.003	**0.57%**	0.004	**1.26%**	0.003	**0.60%**	0.002
Mutual Funds	**0.87%**	0.003	**0.38%**	0.003	**0.62%**	0.005	**0.94%**	0.004	**0.55%**	0.002
Mean Domestic	**0.88%**	0.003	**0.39%**	0.003	**0.61%**	0.005	**1.01%**	0.004	**0.56%**	0.002

The table list LGC of funds as reported by Lipper/Datastream and their respective 5 year mean monthly performance gaps. Sample breakpoints are the same as in Table 6. Performance gaps are calculated by subtracting the Internal Rate of Return of fund flows during the sample periods from the geometric mean return of individual funds during the same period. Conforming to Limited Debt assumption, dollar weighted returns less than -100% are excluded. To avoid influence on extreme values, performance gaps are further trimmed at 1% level. This procedure still leaves 97% of funds with an attainable performance gap. Bold letters indicate statistically significant at 95% level. N/A indicates no fund in sample period has an attainable measure of performance gap.

During all sample periods, fund investors has incurred a significant amount of positive performance gap. The performance gap during 1994-2000 is as much as 1% monthly, which means investors at that period enter and exit the market as wrongly as reducing their annual return by 12%. In other words, they could have been better off by sticking to their funds. The smallest performance gap is seen on 2005-2010 sample. However, it is still economically significant for a 4.68% annual wealth reduction. The performance gaps are similar to documented by Friesen & Sapp (2007) and Dichev & Yu (2011). Another fact is that pension fund investors seems to show poorer timing ability. The performance gaps of pension funds are higher than mutual funds, except for 2000-2005 sample. The performance gap for nearly all fund categories are statistically significant.

2.4 Empirical Findings

2.4.1 Performances and Sensitivities

My main result is shown in Table 2-9. The first column breaks down alpha by sensitivity deciles. As the quality seeking argument of Ippolito (1992) suggest, investors who are aware of managerial quality should be able to digest information from performance residuals, thus they will be awarded a higher risk adjusted return. By my prediction, the most sensitive investors should be selecting funds with higher alpha. Investors who are contrary to manager generated returns should in average selecting inferior funds. The patterns in column one are indeed so. During all but 1994-2000 sample, the mean four factor alpha of funds are nearly monotonically higher as their sensitivity to return residuals become higher. Although equity funds were outperformed by the market during 2010-2015, the most sensitive investors, decile 10, achieved an alpha of -0.069%, significantly higher than decile 1. The t-stats suggest the alpha is less significantly deviated from zero. During 2000-2005, the contrast is even stronger. Funds of decile 10 earns an alpha of 0.453%, which is significantly above mean. It translates to a striking annual abnormal return of 5.44%. Meanwhile, funds held by decile 1 only achieve an alpha of 0.056% percent, which is also barely statistically above zero.

Then I test if there is cross section variation in average fund selection ability across sophistication. The last row in each Panel is the F-probability of a joint test that the mean alpha of all deciles is equal. In Column (1), The null-hypothesis that alpha is identical across investor groups is rejected for all sample periods, although the rejection is weaker for the 1994-2000 sample window. Combined with the monotonic relationship in column (1), the cross-section variation in mean abnormal returns are resulted from the cross-sectional fund picking ability. The finding is consistent to Wermers (2003) where a group of investors is smarter in chasing winning managers. This finding also supports the role of risk adjusted performance as a signal for manager performance, as opposed to fund characteristics like high fees and advertisements (Carhart 1997; Sirri and Tufano 1998; Jain and Wu 2000). The result is not supportive of momentum-riding by which investors stumble upon a lucky momentum strategy that grants them additional short-term profit, as discovered by Sapp & Tiwari (2004), since I have adjusted for momentum factor in the first place.

Column (2) in Table 2-9 shows the estimated performance gaps by sensitivity deciles. Unfortunately, the performance gaps are generally much higher than could be covered by alpha. Column (3) shows negative significant TAAR for all sample-deciles. Investors delegate their investment to fund managers, in an effort to do at least as well as the market. However, their bad timing decisions erode the effort by fund managers significantly. For example, during 2005-2010, the smartest group of investors in terms of fund picking also show an alarmingly higher amount of performance gap of 0.532%. Their TAAR, which is the simple difference between alpha and their performance gap, is highest among peer groups. The performance gap of decile 10 during the first five year of millennium and 2010-2015 is even higher, mounting up to nearly 1 percent per month. In fact, observed from column (1) and column (2), there is a tendency that performance gap is correlated with the stock picking skills of investors, as sensitive investors are punished harder. The F-probability offered in column (2) indeed show a cross sectional difference in timing skills.

Table 2-9 Relationship Between Investor Performance And Sensitivity Deciles For Sample Domestic Equity Funds

	Alpha		Performance Gap		TAAR		TFAAR	
(A) 2010-2015								
Decile	Mean	t stat	Mean	t stat	Mean	t stat	Mean	t stat
1	-0.109%	-15.94	0.861%	85.30	-0.963%	-108.32	-1.066%	-117.57
2	-0.123%	-19.57	0.864%	108.72	-0.983%	-150.78	-1.079%	-159.64
3	-0.123%	-20.87	0.871%	110.12	-0.992%	-147.22	-1.095%	-156.25
4	-0.129%	-14.92	0.880%	102.75	-1.000%	-146.60	-1.101%	-153.29
5	-0.139%	-15.84	0.862%	94.27	-0.994%	-143.66	-1.097%	-146.64
6	-0.138%	-16.11	0.846%	77.36	-0.982%	-109.77	-1.098%	-123.97
7	-0.099%	-9.88	0.891%	86.55	-0.989%	-156.48	-1.097%	-164.71
8	-0.086%	-9.25	0.903%	86.28	-0.983%	-127.82	-1.084%	-138.14
9	-0.089%	-10.56	0.893%	95.95	-0.979%	-133.62	-1.076%	-139.91
10	-0.069%	-7.59	0.921%	78.14	-0.984%	-91.19	-1.080%	-95.98
F Prob	0.00		0.00		0.0951		0.0258	
(B) 2005-2010								
1	0.205%	25.20639	0.350%	38.92667	-0.145%	-25.825	-0.240%	-36.68
2	0.195%	21.05496	0.348%	36.79704	-0.152%	-24.0331	-0.259%	-35.10
3	0.177%	18.79872	0.323%	35.77962	-0.145%	-24.2437	-0.248%	-36.48
4	0.223%	14.28471	0.374%	29.0474	-0.145%	-16.8601	-0.250%	-26.79
5	0.205%	13.39608	0.368%	27.46004	-0.160%	-16.8626	-0.267%	-26.89
6	0.211%	13.63871	0.376%	27.41314	-0.162%	-17.0401	-0.266%	-26.37
7	0.217%	14.62963	0.402%	29.37518	-0.174%	-15.6682	-0.279%	-24.14
8	0.246%	16.74218	0.385%	28.43205	-0.130%	-12.0406	-0.229%	-20.01
9	0.276%	18.68746	0.429%	26.81625	-0.147%	-9.76416	-0.252%	-16.12
10	0.340%	17.04206	0.532%	22.96159	-0.178%	-8.90923	-0.200%	-13.55
F Prob	0.00		0.00		0.0603		0.0323	
(C) 2000-2005								
1	0.056%	1.790997	0.340%	9.689498	-0.290%	-8.34626	-0.392%	-10.47
2	0.095%	4.266576	0.345%	10.17138	-0.248%	-7.27768	-0.348%	-10.05
3	0.084%	3.731383	0.386%	10.86562	-0.299%	-10.9824	-0.400%	-14.71
4	0.097%	3.636534	0.456%	12.59254	-0.354%	-11.3645	-0.455%	-14.26
5	0.126%	5.923585	0.530%	15.08962	-0.398%	-13.2136	-0.506%	-16.41
6	0.171%	6.408445	0.623%	15.02918	-0.439%	-13.7413	-0.538%	-16.54
7	0.164%	6.751855	0.620%	15.14031	-0.438%	-13.6761	-0.536%	-16.22
8	0.207%	8.894533	0.655%	17.15907	-0.441%	-16.1281	-0.548%	-19.59
9	0.261%	8.524804	0.720%	16.08194	-0.445%	-14.3802	-0.551%	-17.09
10	0.453%	14.95116	0.965%	23.55298	-0.484%	-18.2374	-0.599%	-21.97
F Prob	0.0000		0.0000		0.0000		0.0000	
(D) 1994-2000								
1	0.390%	9.76821	1.247%	34.2964	-0.857%	-29.2034	-0.935%	-31.21
2	0.303%	6.402916	1.108%	22.56852	-0.805%	-25.3475	-0.886%	-27.56
3	0.324%	7.648349	1.090%	21.28164	-0.755%	-26.7962	-0.832%	-30.59
4	0.171%	3.952491	0.928%	19.70822	-0.756%	-22.6183	-0.852%	-26.25
5	0.327%	5.358197	0.996%	15.8429	-0.690%	-19.1963	-0.778%	-22.37
6	0.298%	6.635635	1.041%	19.97793	-0.738%	-23.2332	-0.821%	-26.38
7	0.221%	5.236898	0.892%	17.58077	-0.674%	-18.2086	-0.758%	-21.13
8	0.218%	4.921586	0.901%	16.4861	-0.669%	-22.9993	-0.759%	-26.59
9	0.347%	7.317952	0.919%	19.30386	-0.570%	-13.3465	-0.667%	-16.05
10	0.270%	4.931457	0.884%	17.71363	-0.631%	-12.012	-0.739%	-13.91
F Prob	0.0305		0.0000		0.0000		0.0000	

The table includes all domestic equity funds. Sample breakpoints are as of December. Only funds that survived whole sample period are used. Definitions of alpha, performance gap are the same as in Table 6 and Table 8. TAAR is defined as alpha-gap, which measure after-timing gross performance. TFAAR is defined as TAAR-monthly fee, which measures after-timing net performance. F-probability belong to a Wald Test for the hypothesis that mean across sensitivity deciles are identical. Lower F-probability means performance are more diverse across sensitivity deciles.

An intriguing fact is that during 2010-2015 and 2005-2010, the timing adjusted abnormal return do not vary across investor groups, judging from the F-probability in column (3). While I have shown that there is cross-sectional difference in fund picking and timing abilities, those sophisticated investors do not necessarily have a timing adjusted advantage. When considering their loss from wrong timing decisions, they become mediocre compared to peer investors. More extreme happens on 2000-2005 sample. The TAAR for decile 10 is -0.484% per month, which is significantly higher than the 0.290% found on decile 1. Remember they could have stayed put and enjoy a superior alpha of 0.453%.

This finding suggest that investor sophistication is multi-dimensional. Investors that are better in security picking do not mean he is a better timer, since both time-series and cross-sectional performance matter. The negative correlation of fund picking ability and timing ability also suggest that good fund pickers may have been relying excessively on frequent timing, in an effort to further optimize their performance. However, these excessive timing have been detrimental to individuals because the wealth-destruction is significant compared to the gain from extrapolating fund-specific information.

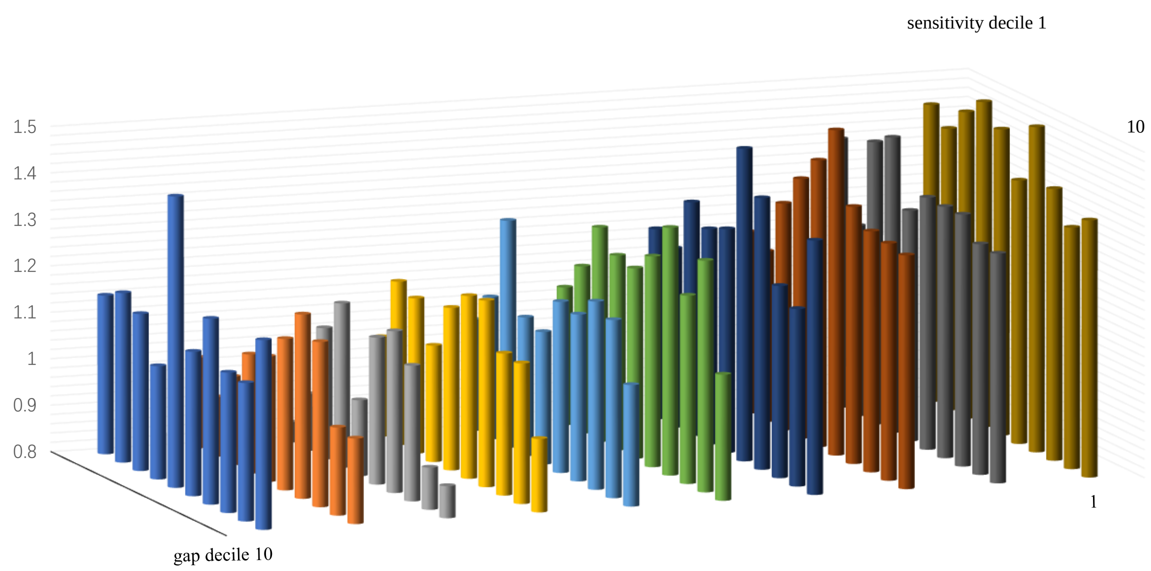
2.4.2 The Choice of Fees

Column (4) of Table 2-9 shows timing and fee adjusted return (TFAAR) for each sensitivity deciles. The TFAAR assumes a monthly carry cost of funds equal to its reported Total Expense Ratio and ignore any other one-off fees like front and back loads. Thus it is a hypothetical after fee performance measure. As we can see in column (4), the performance of investors takes another toll after fees. The average TER are around 1.2% annually, resulting to even lower adjusted returns. However, the mutual fund industry seems to cover the fee they have been paid. The annual four factor alphas are greater than mean TERs in all sample windows. This challenges the notion that market efficiency will push fund industry to an equilibrium where fees will exactly equal to the value managers created (Fama, 1970).

Another pattern is the existence of cross-sectional variation in preference of fees. Fees seems to be related to the fund picking ability of investors. Investors that choose higher alpha funds seems to have chosen the low fee funds as well. During 2010-2015, most unsophisticated investors in terms of fund picking, decile 5 and decile 6, yield lowest TFAAR among peers. The best fund pickers, decile 1 and decile 10, yield the highest TFAAR. The F-probability in column one shows that the inclusion of fees makes the adjusted returns of each deciles different again, although marginally. From the equality in TAAR in column (3), there is a cross sectional variation in fee preference. The same happens in 2005-2010 sample. Column (3) of Panel (B) shows that the TAAR of all deciles are indistinguishable. However, the choice of low fees in decile 8, 9 and 10 make their TFAAR stand out again, thus the F-probability reject an equal TFAAR among these deciles. I do not find an evidence of cross-sectional variation in fee preference during 1994-2000 and 2000-2005 sample, since the F-tests of equal TER on these two samples are not rejected.

Despite the findings of cross-sectional variation in fees, it is subjected to interpretations, since correlation does not mean causation. It could either be that sophisticated investors are intentionally choosing low fee fund to facilitate their frequent timing, or that low alpha funds themselves charge low fees. Thus, we are indistinguishable between whether some group of investors are particularly fee-savvy or they have stumble upon low fee funds by choosing high alpha funds. However, it is hard to believe managers that are paid higher generate lower abnormal returns systematically during as much as ten years.

To illustrate the relationship between performance gap, investor sophistication and fees, I plot them in a three-dimension graph, as shown in Figure 2-3. The height of the cylinders shows mean TER of 100 fund portfolios. The portfolios are formed by sorting both γ_2 and performance gap deciles. The sample period used is 2010-2015 where I have least survivalship-bias. As we can see, fees are negatively related to performance gap. When performance gap is lowest (as in decile 1), the average fees range from 1.3-1.5, a hefty amount among peers. When performance gap is higher, the fees decrease monotonically until decile 9, where investors pay only 0.9-1 percent. Another pattern is that fees are related to investor sophistication. The middle deciles, exactly the group who earn lowest alphas during 2010-2015, seems to pay more than others. The most expensive group of funds, with mean TER over 1.5%, is chosen by gap decile 3 and sensitivity decile 6. The tail ends of sensitivity groups tend to choose low fee funds. When performance gaps are high, the sophisticated investors choose even lower fees, as shown in performance gap 7, 8 and 9.



Funds are separated into 10 deciles by both sample mean performance gaps and sensitivities. Decile 1 contains funds with smallest values and Decile 10 contain funds with largest values. Sensitivity Decile 1-5 have negative sensitivity and decile 6-10 have positive sensitivity. Height of cylinder represent the mean Total Expense Ratio of the overlapping portfolios.

Figure 2-3 Mean Total Expense Ratio by Sensitivity and Performance Gap Deciles, 2010-2015

Although I cannot draw a concrete conclusion that smart investors intentionally choose low fee funds, the additional relationship in Figure 2-3 among performance gap and fees seems to tell a similar story. The sophisticated investors not only choose the best funds. They also rely frequently on timing to strive for the best investment outcome, although they are not generally reaching their goals. However, since they are frequent timers, they also try to shun higher fee funds to avoid carrying costs incurred by holding these funds. As a result, they regain some of their advantage by being smart on fee choices.

2.4.3 Determinants of Performance Gaps

In order to investigate the determinants of performance gap, I run a cross-sectional regression of performance gap on several fund and investor characteristics in Table 2-10. Again, the sample is 2010-2015 with 7016 domestic equity funds. To avoid the influence of extreme value, the performance gaps are trimmed at 1% level. Model 1 include the fund factor loadings calculated by Equation 6 in order to examine the relationship between fund styles and performance gaps. Model 2 includes the realized risk of fund during sample period. The risk is the root of average squared return of a fund during sample period, with same unit as return. Model 3 include two dummy variables which shows either average investors on the fund is contrary or momentum to the return residuals. A fund is a contrarian fund if its γ_2 falls into the first quintile. A fund is a momentum fund if its γ_2 falls into the fifth quintile. Model 3 includes age, a variable that counts the months since its inception to the first month of our sample, and pension, a dummy for pension funds. Model 4 further includes Size, the natural logarithm of average fund AUM during the sample and Expense Ratio, the average fund TER across sample. The specifications of the models are similar to Friesen & Sapp (2007).

Model (1) shows that fund styles alone is a determining factor for performance gap. The four factor loadings explain as much as 43% of cross section dispersion in performance gaps. Investors in high beta, large cap, growth and momentum funds exhibit larger performance gap, as can be read on the sign and significance of their coefficients. The economic significance of market risk and momentum style are high. The findings are qualitatively similar to Kumar (2009), in which individual investors are found to prefer lottery-like stocks with high risk, higher past return and “glamour” feature. Although I cannot equate performance gap from loss in gambling, investors are indeed losing more money by trading funds with these styles. Interestingly, model (2) shows that low risk funds have higher performance gap, and the inclusion of risks axed 1/3 of the economic significance of Momentum loading. Model (3) add two characteristics of investors. We can see that investors with highest γ_2 have higher performance gap, a phenomenon I have discussed in above section. These investors are assumed to be the sophisticated investors. The contrarian investors have lower performance gap; however, the significance is only marginal. Model (4) shows that old fund and pension fund show consistently higher performance gap. Model (5) shows that performance gaps are found on low fee funds, confirming my conjecture that frequent timers may use low fee fund to avoid drag on performance. All the characteristics other than styles explain only 12.5% of performance gap, while the fund styles explain 43.3%.

Table 2-10 Cross Sectional Regression of Performance Gap on Determining Factors

Model	1	2	3	4	5
Beta1	0.8410***	1.0018***	1.0036***	0.9807***	0.9304***
	(0.0596)	(0.0425)	(0.0424)	(0.0423)	(0.0446)
Beta2	-0.1070***	0.1688***	0.1690***	0.1766***	0.2025***
	(0.0137)	(0.0154)	(0.0154)	(0.0152)	(0.0156)
Beta3	-0.3980***	-0.4393***	-0.4375***	-0.4302***	-0.4352***
	(0.0182)	(0.0173)	(0.0172)	(0.0171)	(0.0173)
Beta4	1.5918***	0.9744***	0.9700***	0.9657***	0.9431***
	(0.0648)	(0.0516)	(0.0515)	(0.0515)	(0.0525)
Risk		-0.2373***	-0.2383***	-0.2396***	-0.2452***
		(0.0101)	(0.0103)	(0.0102)	(0.0106)
Contrarian			-0.0002*	0.0000	-0.0001
			(0.0001)	(0.0001)	(0.0001)
Momentum			0.0003**	0.0004***	0.0003**
			(0.0001)	(0.0001)	(0.0001)
Age				0.0001***	0.0001***
				(0.0000)	(0.0000)
Pension				0.0005***	0.0002**
				(0.0001)	(0.0001)
SIZE					0.0000*
					(0.0000)
Expense Ratio					-0.0007***
					(0.0001)
Constant	0	0.0077***	0.0077***	0.0069***	0.0085***
	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Adj. R2	43.30%	53.10%	53.30%	54.40%	55.80%

Beta1, Beta2, Beta3 and Beta4 are calculated as in Section 2.3.3. Risk is the root of mean of squared monthly returns of a fund during sample period. Dummy Contrarian equals one if a fund belongs to the bottom sensitivity quintile. Dummy Momentum equals one if a fund belongs to the top sensitivity quintile. Age is number of available observations for a fund in months. Pension is a dummy for pension funds. SIZE is the natural logarithm of mean total net assets. Robust standard errors are in parenthesis. *, ** and *** indicate significance at 90%, 95% and 99% level.

2.4.4 Relationship between Performance Gap and Trading Frequency

The last two sections show that performance gap constitute a significant proportion in investors performance. However, I have also emphasized that the performance gap is both function of timing and magnitude of cash flows and frequency of cash flows. The measure of gap during the last two sections mimic the trading behaviour of investors who balance his portfolio exactly monthly. What would I have found if I adopt a different frequency? In this section, I change the occurrence of cash flows per year to mimic the hypothetical performance of market timers to different extents.

Table 2-11 Mean Performance Gap of Hypothetical Investors with Different Trading Frequency

Frequency	2010-2015		2005-2010		2000-2005		1994-2000	
	Mean	Std.	Mean	Std.	Mean	Std.	Mean	Std.
Monthly	0.88%	0.003	0.39%	0.004	0.61%	0.014	0.63%	0.027
Quarterly	0.84%	0.006	0.24%	0.017	0.13%	0.022	0.21%	0.024
Half Year	0.74%	0.035	0.11%	0.039	0.08%	0.018	0.19%	0.023
Yearly	0.58%	0.025	0.11%	0.028	-0.17%	0.051	0.12%	0.024
Bi-Yearly	-0.51%	0.190	-0.61%	0.069	-1.34%	0.130	-0.46%	0.176

The table use various ks as shown in Equation 4 to calculate performance gaps. Then performance gaps with different ks are averaged among all domestic equity funds survived in each sample periods. Monthly frequency assume investor flows happens at each month ends. Quarterly frequency assume investor flows happen at each quarter ends, with all flows between quarter ends omitted, and so on.

In Table 2-11, the hypothetical investor is assumed to balance at different frequency. For example, in quarterly frequency, the IRRs are calculated using only observations of cash flows at each quarter ends. In yearly frequency, all cash flows except one at the end of the year is assumed to be absent. Then, the IRRs are compared to the buy-and-hold returns again. Note that if I choose a frequency which result to only one transaction, the calculation becomes trivial and our IRR will be identical to the buy-and-hold return. The table shows dramatic improvement in performance when investors simply trade less. When balance frequency reduces from monthly to quarterly, the performance gaps are already marginally reduced. For example, during 2005-2010, investors recover 0.15% per month by trading four times per year. During 2000-2005, the performance gaps are slashed by 1/6. At half year and yearly frequency, the performance gaps are becoming very close to the geometric returns. During 2000-2005, the investors as a whole are even doing a little bit better than the buy-and-hold returns in yearly frequency. Interestingly, at two-year frequency, the investors in every sample period achieve return higher than buy-and-hold returns. In 2010-2015 sample, investors beat buy-and-hold strategy by 0.51% per month, higher than the loss in alpha (-0.143%) during that period. By active adjustment of portfolio, they recover the loss of bad managers and optimize their performance. In 2000-2005 sample, the gain from bi-year trading is more extreme. Investors outperform their own managers by an impressive 1.43% per month. I attribute the extreme outperformance of bi-year rebalance to two reasons. Firstly, they could be mere luck, since there are only four observations used in calculating bi-year IRRs. Secondly, the investors may have enjoyed the January Effect by entering the market exactly at end of every year.

Table 2-12 Mean Performance Gap of Various Frequencies by Sensitivity Deciles

	(1) 2010-2015					(2) 2005-2010				
Sensitivity Decile	Monthly	Quarterly	Half Yearly	Yearly	Bi-Yearly	Monthly	Quarterly	Half Yearly	Yearly	Bi-Yearly
1	0.85%	0.70%	0.62%	0.30%	-1.00%	0.42%	0.23%	0.24%	0.16%	0.04%
2	0.86%	0.80%	0.65%	0.42%	-0.88%	0.34%	0.31%	0.31%	0.30%	0.20%
3	0.87%	0.76%	0.77%	0.58%	-0.24%	0.34%	0.29%	0.29%	0.29%	0.11%
4	0.88%	0.83%	0.79%	0.69%	-0.17%	0.34%	0.32%	0.10%	0.30%	0.16%
5	0.86%	0.72%	0.71%	0.59%	-0.27%	0.34%	0.25%	0.26%	0.25%	0.03%
6	0.84%	0.60%	0.62%	0.56%	0.11%	0.38%	0.29%	0.26%	0.26%	-0.15%
7	0.89%	0.77%	0.71%	0.61%	-0.32%	0.37%	0.24%	0.25%	0.20%	-0.56%
8	0.91%	0.70%	0.66%	0.61%	-0.55%	0.40%	0.23%	-0.02%	-0.05%	-1.15%
9	0.89%	0.84%	0.69%	0.56%	-0.90%	0.43%	0.21%	-0.09%	-0.14%	-2.23%
10	0.90%	0.79%	0.62%	0.32%	-1.67%	0.48%	0.04%	-0.48%	-0.53%	-2.86%
F	5.47	2.06	0.87	5.06	4.63	17.41	2.1	4.01	9.42	25.15
F Prob	0.0000	0.0298	0.5541	0.0000	0.0000	0.0000	0.0259	0.0000	0.0000	0.0000
	(3) 2000-2005					(4) 1994-2000				
Sensitivity Decile	Monthly	Quarterly	Half Yearly	Yearly	Bi-Yearly	Monthly	Quarterly	Half Yearly	Yearly	Bi-Yearly
1	0.34%	-0.27%	-0.26%	-0.24%	-0.26%	1.25%	1.14%	1.03%	0.74%	0.06%
2	0.35%	-0.15%	-0.15%	-0.14%	-0.34%	1.11%	0.99%	0.90%	0.67%	0.21%
3	0.39%	-0.01%	-0.02%	-0.06%	-0.70%	1.09%	0.99%	0.90%	0.69%	0.03%
4	0.46%	0.04%	0.02%	-0.22%	-0.30%	0.93%	0.74%	0.65%	0.45%	0.18%
5	0.53%	0.16%	0.13%	0.06%	-0.24%	1.00%	0.92%	0.82%	0.64%	0.18%
6	0.62%	0.21%	0.17%	-0.05%	-0.49%	1.04%	0.98%	0.87%	0.61%	-0.17%
7	0.62%	0.23%	0.17%	-0.20%	-1.59%	0.89%	0.77%	0.60%	0.51%	0.22%
8	0.65%	0.17%	0.11%	-0.38%	-2.52%	0.90%	0.75%	0.67%	0.48%	0.10%
9	0.72%	0.27%	0.21%	-0.15%	-2.49%	0.92%	0.77%	0.65%	-0.51%	-0.11%
10	0.96%	0.68%	0.43%	-0.27%	-4.70%	0.88%	0.51%	0.40%	0.05%	-2.15%
F	5.57	2.17	4.26	7.19	11.11	5.75	5.89	5.03	1.72	4.89
F Prob	0.0000	0.0212	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.081	0.0000

The table use various ks as shown in Equation 4 to calculate performance gaps. In addition to Table 11, performance gaps for various k and various sensitivity deciles are calculated so that it reveals pattern of timing improvements on different sophistications. F-probability belongs to a Wald test for identical performance gaps across sensitivity deciles. Lower F-probability indicates higher divergence in timing abilities across investor groups.

The data in Table 2-11 show a consistent pattern: the monthly performance gaps are accumulation of many bad timing decisions. Investors are particularly good at entering the market when expected returns are low and exit the market when expected returns are high. The more investors try to time the market, the more performance gap will incur. The patterns fit previous evidence that individual investors chase returns (Karceski 2002; Sapp and Tiwari 2004; Friesen and Sapp 2007; Bailey, Kumar and Ng 2011; Berggrun and Lizarzaburu 2015).

2.4.5 Improvements on Timing Performance by Investor Sophistication

If frequency traders can benefit from trading less, I am curious to examine separately the dynamics of these processes of different groups of investors. These patterns will tell us which group of investors are more likely to be jeopardized by deviating from buy-and-hold paradigm suggested by efficient market theory, or alternatively which group will benefit more from trading less. In addition, the result will also reveal the association between timing ability and fund selection ability.

Table 2-12 breaks up Table 2-11 by γ_2 deciles. The last two rows in each panel is an F-test that all deciles have the same performance gaps. The F-test aims to detect cross sectional divergence in timing ability in different trading frequencies. In Figure 2-4, I draw the mean performance gaps of different samples into graphs.

Panel (1) to (4) of Table 2-12 shows an intriguing pattern: The improvements on performance gaps are largely driven by sophisticated investors. When trading frequency is reduced, performance gaps of sophisticated investors shrink quicker. For example, in 2010-2015, there is a statistical divergence in timing ability if we assume monthly rebalance, observed from the F-statistics of 5.47. The sophisticated investors, decile 8-10 and 1-3, experience higher performance gaps than the middle deciles. However, when trading frequency is reduced, their performance gaps are also reduced relative to the unsophisticated investors. By half-year frequency, we are indistinguishable between their timing abilities, judging from an F-probability of 0.5541. When yearly frequencies are adopted, the performance gaps start to be smaller for sophisticated investors. When bi-yearly frequencies are adopted, there is a dramatic outperformance of sophisticated investors. The decile 10 in this scenario outperform their managers by a striking 1.67% per months, while the decile 6 still have some positive performance gap. FromFigure 2-4, it is exactly the case for every sample period, since the slope for performance gaps are downward. The reward for the most sophisticated investors by trading bi-yearly is 2.86%, 4.70% and 2.15% for the other three samples, while the most unsophisticated is barely earning anything more than their funds by trading bi-annually. Learning from the F-probabilities, we can know that the turning points performance gap seems to be between quarterly and yearly.

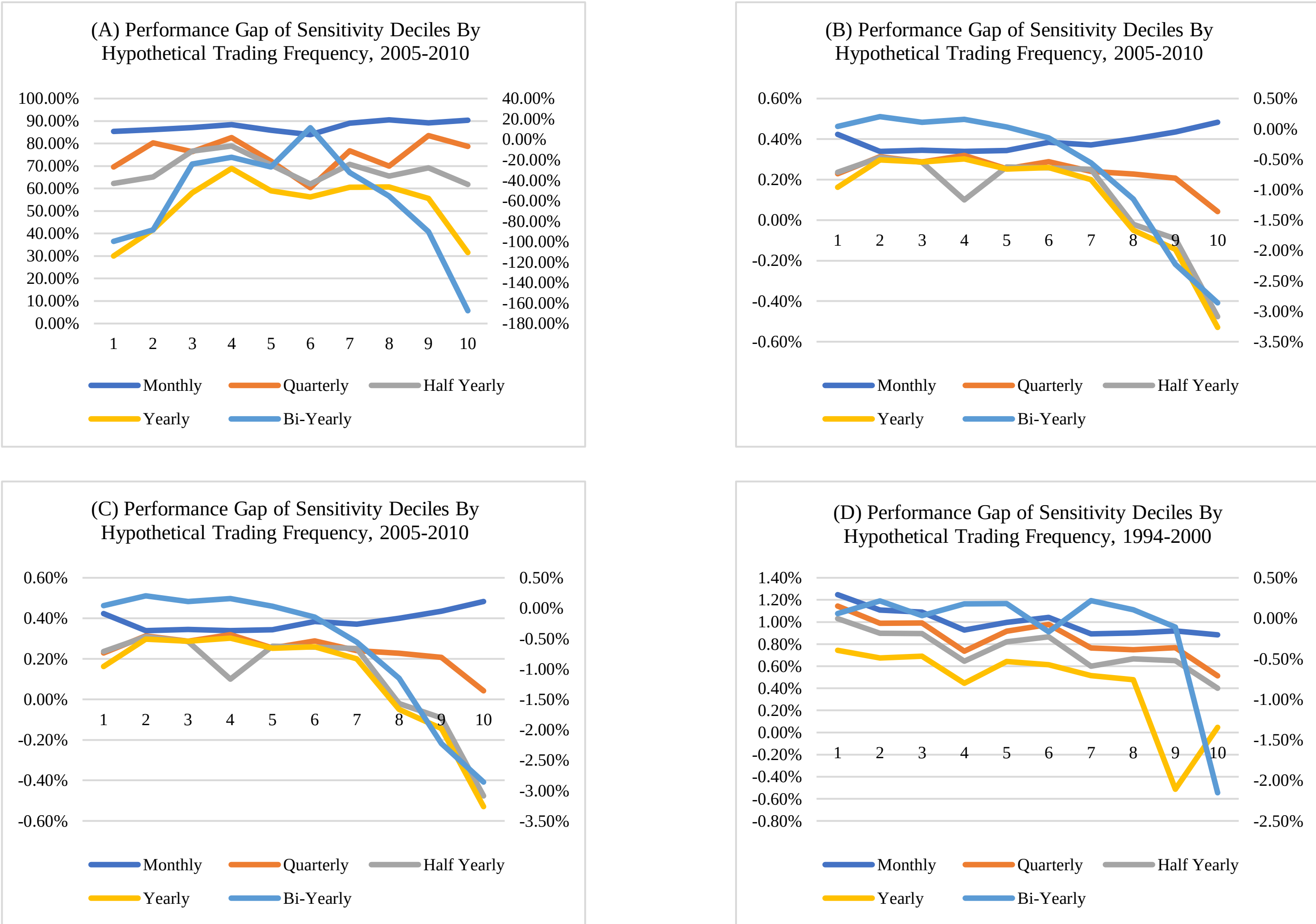


Figure 2-4 Performance Gap of Sensitivity Deciles by Hypothetical Trading Frequency

*Bi-Yearly performance gaps drawn on secondary axis.

These patterns show that when sophisticated investors trade less, they seem to have made some exquisite transactions that time the market very well, showing some long-term timing ability. However, when they trade more, their mistakes accumulate and amounts to terrible loss. I do not observe a significant long-term timing ability on unsophisticated investors since their gain from avoiding frequent trading barely brings their performance gap above zero. That is to say, when these investors trade more, their performance only become bad to worse. I could carefully draw a conclusion that timing ability and fund picking ability is somewhat related. Good fund pickers also seem to be a good market timer, however if they rely too much on market timing, their advantage would vanish quickly.

2.5 Discussions and Conclusions

An intriguing finding in Table 2-9 and Figure 2-3 is that performance-sensitive investors are associated with lower fee funds. As I proxy sophistication with performance sensitivity, sophisticated investors act as if they avoid high fee that direct affect their bottom line performance.

This evidence is consistent with previous evidence on information inefficiency of mutual fund market. Grossman (1976) and Grossman & Stiglitz (1980) propose that in a costly information setting, the market is efficient to the point that abnormal return earned by investors compensate their cost of obtaining information. For the mutual fund industry, any manager who earn abnormal return may pass the information discovery cost to investors in the form of fees, so that high fee funds earn higher abnormal return. The more passive a fund's strategy is, the less fees it will charge since less resources are directed in discovering information. Another implication of this theory is that change in performance of various measures must be commensurate with change in fees by force of the market efficiency.

However, there is abundant documentation that mutual fund market is not information efficient (at least in this setting). Dating back to Elton et al. (1993), it is already a known fact that expensive funds do not earn back their compensations and cheap funds do not necessarily offer inferior returns. Gruber (1996) uses the established Three Factor Model to adjust for risks. He finds that worst performing funds during the sample provide alpha of around -2.5% per month yet charge the highest fees, which is around 1.5% per year. He also finds that for top performing funds, expense goes up slower as compared to expense going down for bottom performing funds. More evidence on this issue can also be found in the introduction section.

The information inefficiency in mutual fund market suggest it is rational to follow a low-cost strategy, as Carhart (1997) motivates in his paper. In our study, the sophisticated investors indeed follow this strategy. The F-probabilities in Table 2-8 shows that better choice of fees offsets the worse timing performance of these group of investors.

These performance sensitive investors are not also fee sensitive for no reason. Christoffersen & Musto (2002) emphasize the importance of distribution channel on the behaviour of mutual fund flows. They describe an industry where unsophisticated investors are mostly either introduced by third-party advisors or appealed by advertisements, while sophisticated investors rely on rational judgements to invest in funds. Unsophisticated investors are unable to form rational judgements because of information asymmetry. The different distribution channels result to difference in participation cost- unsophisticated investors end up pay more fees, which either comprise of advisory fees, commissions or management fees. The view are consolidated by Huang et al. (2007), where they states that participation cost is central to rationality of investment process. Guercio & Tkac (2002) add that whether a decisional body exist also help investors to be more aware of the pricing of funds.

However, this finding is also subjected to an alternative interpretation: sophisticated investors are defined on their fund selection skills. Several studies have shown that fees are inversely correlated with performance. As they choose funds with better risk adjusted returns, they may have luckily chosen fund with lower fees. There is possibility that sophisticated investors focus solely on performance while ignoring fees. The chicken-and-leg paradox can be resolved by examining whether the predictive relationship between fund flows and fund performance can be replaced by fund flows and fees. Gruber (1996) has done that and he finds fees as a weaker predictor.

Another finding in this chapter is the dramatic improvements on investment outcomes for sophisticated investors if they rebalance with a lower frequency. This is a novel finding. Despite there are many evidences in previous studies on the detrimental effect of excessive trading frequencies on long term wealth, none have related the sophistication of investors to the benefit of not trading excessively. If sophisticated investors have more room to improve than unsophisticated investors, their superior timing ability may be hidden by the excessive rebalance frequency. As the time-varying nature of expected return of financial assets are widely documented, one must not rebalance in excess of the degree that expected returns are changing. Previous studies do point out expected returns are slow-moving, for example the study on equity premium. The success to market timing is not only to enter the market when expected return is high, but also understand how often do expected returns revert.

The study also sheds light on the cross-sectional dispersion in timing ability. Interestingly, sophisticated investors have a worse timing ability than unsophisticated investors, reflected in their mean performance gaps. This suggest investor sophistication in fund market is multi-dimensional. Gruber (1996) speaks of a dichotomy that sophisticated investor make decision on fund performance and unsophisticated or disadvantaged investors base investments on other factors. As a result, these sophisticated investors are able to optimize their financial performance. What I find shows that these performance-sensitive investors indeed earn high alpha, however they are penalized on below-par timing decisions.

The final conclusion of the chapter is to evaluate the fund investing process comprehensively, since the three aspect to fund investment: selection, timing and fee may materially alter your outcome. A fund is only as good as the performance after fee, and an investor is only as good as his timings. It also offers advice to studies on individual fund investors in the future. The return from fund they choose is only nominal, since investors has discretion over what fee he accepts and how often he may trade. The study on investors is not completely identical to the study of funds after all.

CHAPTER 3

Does the Flow-Performance Relationship Change Throughout the Year?

Chapter 3 - Does the Flow-Performance Relationship Change Throughout the Year?

Abstract

The non-linearity of flow-performance relationship is widely discovered and explained among mutual fund studies. However, little focus on how the relationship changes throughout the year. This chapter brings several calendar-related factors which may cause the linearity into attention, including tax planning and annual portfolio rebalance. I use several approaches to model the shape of flow-performance function during the year and find that it does change substantially. The linearity is relatively flat during the year than end of year, which I believe is attributable to a mixture of year end rebalance and tax-loss selling. Using information in the cross-section, I construct variables that mimic investors' actions on gains and losses throughout the year and the results consolidate the tax and rebalancing story. In a further test, I find that at end of year, small, risky, advertised and income fund receive greater flows. Fees, age and initial investment requirement do not have a statistically significant effect on flows at end of year.

3.1 Introduction

The relationship between flow and performance in the mutual fund industry is under constant scrutiny in academic field. Representing investor's allocation decisions, investment flows to and out of funds reflect their evaluation of the fund quality. As the primary concerns of investors is on whether the funds could generate long lasting profits, it is not hard to imagine that flows may be related to track records of the funds. Although the economic relevance of track record of the funds is still debatable, academics generally find a positive correlation between flow and recent performance (Ippolito 1992; Warther 1995; Sirri and Tufano 1998; Fant 1999). Many argue that the correlation are caused by the rational learning of investors (Berk and Green 2004; Huang, Wei and Yan 2012). Some evidences of persistence in fund returns (Grinblatt and Titman 1992; Bollen and Busse 2005; Berk and Tonks 2007) give the investor learning view economic support.

Academics are also interested in exploring the conditional effect of performance on the flow-performance relationship. A widely-observed discovery is the convexity of flow-performance relationship. The flows are extremely sensitive to best performers while inert towards poor performers. This asymmetry in investor behavioural raises question on the efficiency of the mutual fund market since it shows that the best managers draw the lion's share while the worst managers are not adequately punished. Past literature made efforts to explain the convexity issue, for example anticipation of strategic change (Chevalier and Ellison 1997), information costs (Sirri and Tufano 1998; Jain and Wu 2000; Huang, Wei and Yan 2007), strategic fee settings (Gil-Bazo and Ruiz-Verdú 2009), investor sophistication Ferrei*ra et al* 2012) or tax (Bergstresser and Poterba 2002)

These literature focus specifically on explaining the convexity by calendar months. Despite a plethora of papers examine the calendar effects in equity market, it is surprising that little efforts have been made towards this direction in mutual fund research. This study investigates the conditional effect of calendar months on the flow-performance relationship. The flow-performance function is shown to change materially throughout the year.

The choice of calendar month as a potential determinant of flow-performance relationship is not arbitrary due to several reasons. Pioneer papers in equity research have established some corner stones. Firstly, mutual funds, registered as investment companies in the United States, has their own tax year. Unlike common companies, the Tax Reform Act (TRA) of 1986 unifies the tax year end of all investment companies to October 31st. In addition, TRA stipulates that to pass-through all capital gain taxes to investors and avoid taxed at fund level, mutual funds must distribute most of the realized net capital gains and dividends obtained before October 31st. The importance of tax-year end and its affiliated effect on equity market like January Effect are widely discussed in the past (Haug and Hirschey 2006). There is also evidence on the implementation of TRA affecting calendar effects in the equity market. He & He (2011) finds there is a tendency January Effect is replaced by November effects, due to concentrated tax-loss selling of investment companies in October. For individual investors, if the fund is held in a taxable account, the deadline for receiving a tax form for all realized capital gains and fund distributions is December 31st. There is motivation for investors to hold good performers till next year to avoid being taxed for short term capital gains and sell loser funds for tax-loss harvesting. Thus, investors may react differently to fund performance and distributions at turn-of-the-year.

Institutional and household investment planning could also alter flow-performance relationship. Both anecdotal and academic evidences suggest that institutions and individuals often review the year-to-date performance of their portfolios at the turn of the year. For this reason, the purchase and sell decisions are often made at the turn of the year in accordance with several concerns like tax, investment prospect, risk appetite, liquidity and strategic change. Some papers also document window dressing behaviours at turn of the year in which institutions sell off their losing investments before financial year end to avoid embarrassments (Sias and Starks 1997; Ling and Arias 2013). In addition, magazines and newspapers publish their annual rank of mutual funds. Thus, year-to-date performance, measured in both gross or risk-adjusted terms, may be salient to consumers. These "star" funds may be able to attract flows once their ranks becomes publicly available and empirical evidence find this is the case (Jain and Wu 2000; Barber, Odean and Zheng 2005; Chen, Adams and Taffler 2013). Chevalier & Ellison (1997) documents that fund managers increase portfolio variance before year end, a gamble to get back to race before year-end rankings.

Portfolio rebalance may also alter the behaviours of flows. Conventional wisdom recommends annual portfolio rebalance at year-end since fluctuations of asset prices throughout the year results to different asset weights compared to target risk-return profile. Common portfolio rebalance strategies suggest that one buy more losing investments and sell gainers to maintain their original weights. A few studies find that portfolio rebalance is commonplace. For example, Calvet et al. (2009) finds that household investors fight passive variations in asset prices by active rebalancing. Jank (2012) documents that aggregate mutual fund investors act according to economic signals. They tend to exit the market when economic conditions are bad and enter the market when economic conditions are good. Portfolio rebalance is contrarian by its nature. This is conflict with tax-loss harvesting by which selling losers and keeping winners is optimal (Shefrin and Statman 1985). Portfolio rebalance and tax-loss selling implies different behaviours which creates competing hypothesis. Furthermore, there are two confounding effects that has similar predictions to portfolio rebalance (Shefrin and Statman 1985). One is disposition effect, and another is an (unjustified) believe in mean-reversion. Disposition effect describe the psychological bias that investors tend to hold on to losers but sell winners too early. The belief in mean reversion motivate investors to buy losers and sell winners. These two will also predict contrarian behaviours.

Several recent studies also emphasize a behavioural aspect to calendar month that alter the flows. Thaler (1980) and Shefrin & Statman (1985) discuss the role of self-control as an offsetting mechanism to disposition effect. As the deadline for tax year end draws near, investors may switch from their habitual behavioural pattern (disposition effect) to a rational mode in which tax concern dominates, a process call self-control in behavioural science .

Kamstra et al. (2017) also find a strong seasonal pattern in asset allocation of mutual fund investors closely resembling one exhibited by Seasonal Affective Disorder (SAD). The autumn months saw onsets of SAD symptoms and intriguingly, an exodus from risky funds as well. In contrast, the spring months marks a period of increasing risk appetite.

The above-mentioned factors reveal a complex web of economic decisions on which many hypothesises are testable though hard to disentangle. Nevertheless, they all point to the potential significance of calendar month for investment flows. In This study, I use piecewise linear regression model to measure sensitivity of return to each part of performance (defined by abnormal return and raw return). Unlike previous papers which use monthly or quarterly data of every month, the regressions are run each month at cross-section level. This methodology not only show the flow-performance function at each month, but also which group of funds are winning shares and which group are losing shares. When performance is defined on rolling CAPM alpha, the average flow-performance function across the year is a traditional convex shape similar to Sirri & Tufano (1998) and Chevalier & Ellison (1997). However, the shape of the function changes materially across calendar months. The most drastic change happens at December when, surprisingly, flows become significantly contrarian to poor performance, turning its sensitivity to poor performance highly negative. Meanwhile, the sensitivity of flows to highest alpha quintile are higher than other times of year. A hand check of the data show November and December are months with high net inflow of mutual funds. The regression indicates that these inflows favour extreme performers at year end. The inherent structure of panel regression also suggests a reallocation of flows at year end: extreme good performers are gaining money and mediocre performers are losing money.

I also check if the choice of factor models matters for the flow-return function, since asset pricing papers identify factors other than the market and investors may use these more sophisticated models to adjust for risk. I collect data on Fama & French (1993) three factors plus a 12-month momentum factor discovered by Carhart (1997) and compute rolling alphas on three factor or four factor model. The flow-performance function remains qualitatively unchanged across the year compared to result obtained through CAPM alpha. A minor difference is that investors are more sensitive (less contrarian) to highest (lowest) three and four factor alphas quintiles than CAPM alpha.

When performance is defined by gross return, the result is slightly changed. Flows show generally positive sensitivities to extreme 12-month return, indicating flows are punishing worst annual performers and chasing best annual performers, a pattern proposed by Berk & Green (2004). In addition, when performance is measured by monthly return, flows are contrarian to worst performers. However, regression coefficient of monthly return shows that a large part of contrariness to worst performers is shown at November and December, when larger drop in fund NAV coincides with large inflows.

These findings on flow-performance relationship at year end shows a different picture from what depicted by traditional mutual fund studies. The proposition in Berk & Green (2004) is that flow should punish funds with poor abnormal return and reward funds with good abnormal return. Under the assumption of diseconomy of scale, positive alpha funds attract too much capital and their future performance will attenuate. Negative alpha funds maintain a healthy portfolio size and they suffer less from diseconomy of scale. What suggested by our data is that in average, these poor performers are not adequately punished, and most of the effect comes from excessive flows to them at December (and partly November), for some unknown reason. Meanwhile, the best funds enjoy significantly higher growth rate in assets, especially at year end, consistent with the information cost hypothesis of Sirri & Tufano (1998), who emphasize that year-end rankings are salient to consumers.

In later sections, I explore the reasons why flow-performance sensitivities vary by calendar month. I emphasize behaviours of gross flows rather than net flows. The reason is stated below. Due to the coexistence for many testable hypothesis, flow-return sensitivities do not tell us the whole picture, since the coefficient from regression is an average measure of sensitivities of inflows and outflows to performance. It is possible that the purchase and sell decisions are driven by different factors and the usage of net flows smear this information out. The understanding of gross flow is important, since many of our hypothesis has specific predictions on purchase and sell patterns of mutual funds. For example, tax-loss selling predicts that the funds with more year-to-date capital losses should experience more redemption than sales when tax year end approaches, as investors eager to harvest these losses to offset capital gains. Tax-loss selling also predicts that best performers are kept until January as investors wait for short term capital losses to become long term (Constantinides 1983). In contrast, Shefrin & Statman (1985) argue that disposition effect has a competing prediction that investors are eager to sell gains and ride losses. They also mentioned that a belief in mean reversion and portfolio rebalance may coincide with the patterns predicted by disposition effect.

Many studies do recognize the value of using gross flows over net flows, and the analysis is commonly done through unique micro data (Odean 1998; Dhar and Zhu 2006; Bailey, Kumar and Ng 2011). Unfortunately, I do not have access to these datasets. There are also concerns on these datasets. Firstly, many studies (like Grinblatt and Keloharju 2000, 2009) share the same dataset, which produces potential data snooping issue. Secondly, it is a common practice for US studies to use the gross flows on SEC filings, which is quarterly or even semi-annually. These frequencies do not match the required frequency of this study. Thirdly, micro data usually cover much shorter time periods than aggregated data. Thus, to specifically deal with flow-performance relationship of inflows and outflows, I developed a measure called PGR (probability of gains realized) and PLR (probability of gains sold) from similar studies like Odean (1998) and Chang et al. (2016). PGR measures the proportions of funds with outflows associated with positive returns in the same month and PLR measures the proportions of funds with outflows associated with negative returns.

The result provides mixed evidence on tax-loss selling. The PGR for mutual funds falls from January until December almost monotonically, suggesting investors are more inclined to hold on capital gains when they are still short-term. However, this pattern is both predicted by tax-loss selling and year end return chasing. Meanwhile, the result on PLR shows that from January, investors increase their realization of capital losses right until October, a time coincides with investment companies facing their TRA tax confirmation deadline. After October, there is a strong tendency that the losing funds are bought back: the PLR plummet to below 50%, which is consistent with our previous regression results.

I also design a measure of the probability of a certain performance quintile is sold called PS (probability of being sold). Gross returns are sorted into quintiles by each month and the percentage of funds with outflows are computed on each quintile. PS capture the shape of flow-return function while considering both inflows and outflows, although it is a pseudo measure of gross flows. Result on PS consolidates our findings from piecewise regressions. For funds with extremely poor return (quintile 1), the PS raise drastically until October, and fall dramatically after October. For funds with extremely good return (quintile 5), PS fall monotonically across the year, while the last two months saw a sharper fall.

Until this point, the particular reason for the observed pattern in flow-performance relationship is still unsolved. What caused the extreme contrariness to poor performance at year end, with the turning point being October? What are the attitudes of investors towards gross or risk adjusted return, and how do these attitudes change at turn-of-the year? How does characteristics of funds interact with calendar months to influence the flow-performance relationship? To answer these questions, I resort to formal regressions of flows on measures of performance and various fund characteristics previously found to affect flows. The performance measure includes one, three and four factor alphas, gross monthly and annual returns. The characteristic variables are size, age, fees, riskiness, whether a fund advertise, whether a fund is a growth fund and whether a fund require a minimal investment (a proxy for institutional availability). The regression is done separately for December and other months of the year. The result is as follows: flows are sensitive to all measures of performance in December, as well as ordinary months. However, the explanatory power of CAPM alpha is much higher than three factor and four factor alphas, consistent with the discovery of Berk & van Binsbergen (2016) and Barber et al. (2016). Flows are also highly contrarian to contemporaneous one-month return and contemporaneous alphas in December. Gross returns also have a very special role in December, with the four variables alone explaining as much as 21.4% of variation of flows. The explanatory power of alphas is much weaker. For the rest of the year, performance variables barely explain flows. This suggest that investors are more performance-centric at December.

I also find that at end of year, small, risky, advertised and income (in contrary to growth) fund receive greater flows. Fees, age and initial investment requirement do not have a statistically significant effect. Meanwhile, for the rest of the year, risky and expensive funds experience *outflows*, which is different from turn-of-the-year. Overall, it seems that investors seem to have stronger risk appetite at year end, and their investment becomes highly contrarian.

The structure of the chapter is as follows: Section 2 introduce the background knowledge and review relevant literature; Section 3 contains model specifications and methodology; Section 4 specifies the source and nature of the data; Section 5 shows the empirical findings; Section 6 provide detailed discussions on findings and Section 7 concludes the chapter.

3.2 Literature Review

3.2.1 Flow-Performance Relationship and Its Linearity

There is an established finding in mutual fund study that the investment flow of funds is correlated with their performance, although interpretations defer significantly. Existent explanations are rational, behavioural or institutional.

As early as 1992, Ippolito (1992) finds a clear tendency of money flowing into recent good performers while flowing out of recent bad performers. The performance in this study is defined as the idiosyncratic realization of fund returns. He argues that the correlation reflects consumers' inferring product quality from return series. Using another sample, Patel, Zeckhauser and Hendricks (1994) also find a significant correlation to past performance. Nearly 70 percent of cross-sectional variations of flows are explained by past performances alone. Additional examinations show that 1. Ranked performances have higher explanatory power and 2. Risk adjusted performances do not perform better than gross returns. Given these findings, the authors choose a behavioural inclination: response to recent performance implies a status-quo bias. The higher effect of ranked performance, suggesting investors respond more to readily available information, consolidates this conjecture.

Gruber (1996) believes that the persistence of mutual fund performance justifies the rationality to chase it. The persistence is arguably generated by the skill of manager (which is not priced in the fund net value), since an efficient market would not have allowed such a persistence. Berk and Green (2004) propose that positive flow-performance relationship is essential to the elimination mechanism in fund market. Good funds receive inflows which inflate the assets of the funds. More assets lead to diseconomy of scale which erodes future risk adjusted returns, and vice versa. Later studies holding a rational view, for example Huang, Wei and Yan (2012) tend to conclude that the correlation is created by Bayesian investors learning quality information from fund track record. Huang, Wei and Yan (2012) finds that investor's ability to read track record is infected by the volatility of the fund, which decrease the validity of the information. Choi, Kahraman and MUKHERJEE (2016) and Brown and Wu (2016) document investor learning not only on single fund scale, but also among a family of funds.

Intriguingly, the shape of flow-performance function found in the above studies are mostly convex, with particular emphasis on the good performance region. This means stellar performers are rewarded with disproportionally high inflows and worst performers are not penalized enough. There are numerous papers specifically focus on explanations on this issue. For example, the result of Sirri and Tufano (1998) is that flows are extremely sensitive to performance in top quintile, while statistically not sensitive at all for two bottom sensitivity quintiles. They suggest that attention is the key to the problem. Since investors face high search cost, focusing on the recent best performers is a feasible way to lower search costs. Gruber (1996) propose that the reason why worst performers are not punished enough is due to the existence of a "disadvantaged group" who face institutional or tax constraints that hinder their exit from these funds. Lynch and Musto (2003) argue that the convexity is created by the strategic change of the fund company. The worst funds are likely to change strategy to a better one, which is foreseen by the investors. As a result, they are more likely to wait and stay. Huang, Wei and Yan (2007) shows that funds with low participation costs have a more linear function. High participation cost is associated with less sophisticated investors, for whom recent performance is salient. In addition, investors face transaction cost, a part of participation costs, that prevent transactions only until when performance is extreme. Ferreira *et al.* (2012) develop from their conclusion to document less convex function in more developed countries. Ivkovic and Weisbenner (2009) present evidences that the convexity is created by a mixture of tax and fund picking effects. Inflows are related to fund pickings and outflows are more concerned with taxes. Besides, factors such as redemption costs lower sensitivity of outflows to bad performance. However, alternative results are not uncommon. For example, instead of convexity, Franzoni and Schmalz (2017) finds a hump-shaped function. They explain using a model in which investors are Bayesian. The information on extreme returns are of less quality and investors are rather to stay put facing these extremeness than moderate returns. Spiegel and Zhang (2013) attribute the problem to model misspecifications.

Unfortunately, the existing literature is far from settled in solving the non-linearity issue. Neither the rational learning or behavioural theory dominates. Our study does not impose any constraint on the shape of the function. Instead, I reveal the empirical shape and investigate whether the function form change during the year. In addition, I focus specifically on anything that can be explained by the calendar effect, which is not dealt with in detail in the above studies.

3.2.2 Potential Causes of Calendar Effect in Mutual Fund Investments

3.2.2.1 Taxations of Mutual Funds

The tax treatments for mutual funds determine that turn-of-the-year is a sensitive stage for making trades for either fund investors or investment companies. Under tax, information in performance at end of the year has different implications than ordinary months. This is one of the reasons why I believe calendar months may affect behaviour of fund investors. The section briefly introduces tax settings for US mutual fund industry and why these are related to calendar effects.

Taxations are crucial for mutual fund investments, since for individual's capital appreciation and incomes are treated as ordinary income as if one is holding the original securities. Thus, mutual fund investments are subjected to either income tax or corporate tax, sometimes material. Investment companies, the companies that offer mutual fund products in U.S, are pass-through entities. Pass-through means that most of the income and realized net capital gains before the tax year should be distributed to shareholders. The tax law not only avoids double counting of the taxes, but also prevent mutual fund companies to exploit tax-timing strategies. To avoid being taxed at corporate level, investment companies must distribute more than 98% incomes and realized capital gains. When these proceedings are distributed to shareholders, capital gains are taxed at marginal tax rate for capital appreciations and dividends are taxed at marginal ordinal dividend income rate. While any proceedings of fund companies are passed through, the capital losses are not. The capital losses in a tax year can be realized to deduct realized capital gains from the same year. Unrealized capital losses can remain in fund for capital gain offset for as long as seven years. From the perspective of investors, the tax law treats mutual funds as ordinary financial assets. Thus, individuals are taxed on their mutual fund trades as if they were trading stocks. The rules are the same: If one sell funds that have appreciated in value, they are subjected to capital gain taxes, unless offset by selling losing fund investments.

Individuals and mutual fund companies both receive their tax slips at end of the year, yet the two dates are not identical. For individuals, the tax year end is December 31st. However, the Tax Reform Act of 1987 replace the tax year end for investment companies with October 31st, to reduce instability caused by mass tax-related trading at November and December. There are several studies which discuss the change enforced by Tax Reform Act of 1987 (Barclay, Pearson and Weisbach 1998; Gibson, Safieddine and Titman 2000; Johnston and Paul 2005; He and He 2011). The last two months of the year mark the beginning of the new tax year for investment companies and those are times when most of the funds make distributions.

Since tax on mutual funds could be material and any realized gains and incomes are unavoidable either at individual or corporate level, the key to minimizing the present value of the tax burden lies in timing, or the so-called tax planning. Generally, tax rate for short term capital gains are higher than long term gains. The capital appreciation of a portfolio within the tax year is defined as short term. It is rational for one to delay realization of capital gains until the next tax year, or even indefinitely. Also, given that the short-term capital losses can be used to offset capital gains, it is rational to realize capital losses immediately before the end of the tax year. In asset pricing field, hypothesis has been made on the behaviour of agents facing tax deadlines. Constantinides (1983) show that when short-term and long-term capital gain tax rate is not distinguished, it is rational for investors to gradually increase sale of their losing investments until December.

Shefrin and Statman (1985) study the disposition effect, as well as other confounding effects that affect the trades of individuals. One of the effects is the tax-loss selling effect. The disposition effect predicts that investors are reluctant to sell losing investments and too quick to sell winning investments. However, at the end of the year these investors are facing tax deadlines so that they may do exactly the opposite. They find a mixture of the two effects using empirical data. Odean (1998) also document a mixture of disposition effect and tax minimizing strategy. They find that individuals gradually decrease the tendency for selling winners and increase the tendency for selling losers. They also explain that the reason tax-awareness of investors increases from January to December is self-control, a psychologic mechanism that dominates disposition effect.

The studies above provide both normative and descriptive account on the behaviour of managers or individuals facing capital gains/losses. However, little study takes the perspective of investors alone. Tax law in US stipulates that all distributions are divided equally for all shares, regardless of new or existing. A complicated issue arises: Since investors are taxed on distributions that does not distinguish age of the share, new investors of a fund may be taxed on distributions they do not entitle. For the same reason, new investors may enjoy tax free gains by investing funds that accumulates many historical losses. These losses/benefits are discussed in many tax advice articles on newspapers and magazines.

When the tax implications are made clear, it is possible that the flow-performance relationship would be altered by tax minimizing. Think about the traditional rational learning arguments introduced in 2.1: good recent track record signal good quality of managers, thus flows should buy into these funds; Bad track record signal bad quality, thus flows should flee these funds, creating a positive flow-performance relationship. However, under tax enforcements and certain calendar times when investors face tax deadlines, good performance may signal accumulated, unrealized capital gains, or undistributed incomes. In contrast, funds with bad performance may be attractive since many historical losses is available to offset gains. The attrition of funds also lowers the possibility that investors are taxed on unentitled distributions on purchase. These are the reason why tax may alter the flow-performance relationship and how the calendar effect interacts.

3.2.2.2 Mutual Fund Tournament and Household Investment Planning

Mutual fund tournament and household investment planning are two additional factors that invite calendar effect into flow-performance relationship. However, this argument relies on two assumptions. Firstly, there are information cost in the market. Fund with extreme returns are prominent among peers and they enjoy more investor attention. Similar arguments can be found in Sirri and Tufano (1998). Secondly, I must assume that the executions of investment plans are concentrated in certain time of the year, when the rankings of funds become more salient.

Empirically, these two assumptions are supported by the study on mutual fund tournament. Mutual funds are shown to be competing for annual rankings to gain market share, assets under management and fame. Meanwhile, investors take annual rankings seriously so that star funds at year end gain significantly more market shares. Brown, Harlow and Starks (1996) observe a scenario in which lagging funds gamble for exceptional year-end rankings, or the so-called window dressing. They address that "*Although some of these publications and services rank funds every quarter, the most critical rankings are based on annual performance and are usually produced at the end of the calendar year.*" Chevalier and Ellison (1997) relates the convexity to the incentive of managers to window dress. Ivkovic and Weisbenner (2009) find that inflows are associated with relative performance of funds, suggesting the purchasing decision of investors are associated with the rankings. Berk and Green (2004) provide evidence on the consequences of fund tournament – competitions exhaust investment opportunities and erodes both positive and negative risk adjusted returns. Guercio and Tkac (2002) points out that both pension funds and mutual funds plan their investment at least once a year, preferably at year end.

Mutual fund tournament has direct implications for flow-performance relationship. The annual assessment period for investors also directs most of the effects to end of year. The year-end implications of fund tournament are contrary to tax minimization since investment flows are chasing the best performers without regard to its tax consequence. By the same token, funds with huge capital losses are not considered as treasures but bad quality funds.

3.2.2.3 Portfolio Rebalance

Another reason to believe flow-performance relationship will change throughout the year is portfolio rebalance, When the desired characteristics on the asset change, the investor leaves the asset for another with the original characteristics. Rebalancing not only remains as an academic topic. Countless advices on rebalancing mutual fund portfolios can also be found in magazine or newspaper articles and many of them suggest to do so at least once per year, at the end of year.

One of the characteristics that motivate rebalance could be expected return. The discovery of time-varying expected returns (for example Ferson 1989) lays the theoretical ground for reallocation among securities or asset classes. Several mutual fund studies have documented investors reacting to time-varying expected returns. For example, Jank (2012) finds that equity fund flows are associated with equity premium. Flows can also predict future economic activities. Chalmers, Kaul and Phillips (2013) finds a smart money effect: when economic indicators signal worsening conditions, investors shift from risky funds to safer funds. Also, sophisticated investors are more likely to do so. Kamstra *et al.* (2017) discover a seasonal pattern in fund flows, which he relates to Seasonal Disorder, a rather behavioural explanation.

Portfolio rebalance may also arise from the belief in mean-reversion. Common stock returns are sometimes shown to be mean-reverting in the long term (Cochrane 2009). If asset returns are indeed mean reverting, it is possible to exploit this pattern. Although the agency nature of funds make it unique compared to common stock portfolios, many studies documents that short term success of the funds are very hard to repeat (Elton, Gruber and Blake 1996; Carhart 1997; Kosowski *et al* 2006; Fama and French 2010), meaning they have mean-reverting features. Moreover, there is evidence on deliberate strategic change of loser funds to re-enter competitions (Lynch and Musto 2003). These evidences indicate winning funds and losing funds may be exchangeable in the future. In this light, it is rational for investors to reallocate from winning funds to losing funds.

Diversification offers another perspective to rebalancing decisions. When a fund is performing extremely well (bad), the weight of its market value would be too big (small) compared to what set originally. This may result to a new portfolio with different risk-return profile. From a personal finance view, it is crucial that one keep his portfolio in control. This argument is included in the articles I introduced above. Thus, it may be wise to offload the funds that performs good and buy more into the funds that performs bad.

Since I have listed three factors that motivates the rebalancing behaviours, they are jointly called the rebalancing effect. The rebalancing effect predicts the same flow-performance relationship as the tax effect, since investors are predicted to be contrarian to recent performance. It is hard to disentangle the two, however Odean (1998) is able to do so using micro datasets. While the primary focus of his study is disposition effect in stock market, he finds some tax-loss selling in December. The rebalancing hypothesis is ruled out. With the relatively muted discussion on this matter in mutual fund studies, I am curious to investigate using our mutual fund dataset.

3.3 Methodology

3.3.1 Calculation of Flows and Performance Variables

3.3.1.1 Calculation of Flows

I calculate flows of each funds as such that it reflects the incremental investment into (or out of) a fund after capital appreciations (losses) are accounted for, following established studies on mutual fund flows (Chevalier and Ellison 1997; Sirri and Tufano 1998; Edelen and Warner 2001; Ben-Rephael, Kandel and Wohl 2012). Monthly dollar flows for a fund are $\mathrm{TNA_t} - \mathrm{TNA_{t-1}} * \frac{\mathrm{NAV_t}}{\mathrm{NAV_{t-1}}}$, where TNA is the total net asset for the fund and NAV is the net asset value of the fund. The term $\frac{\mathrm{NAV_t}}{\mathrm{NAV_{t-1}}}$ inflates the TNA of last period by return of the fund, so the term $\mathrm{TNA_{t-1}} * \frac{\mathrm{NAV_t}}{\mathrm{NAV_{t-1}}}$ is the size the fund could have been if investors ride the capital appreciations (depreciations). Also, to fully account for the asset growth of the fund, I normalize dollar flows using TNA of last period. Therefore, the measure of flows in this study is:

$$Flow_{i,t} = \frac{DollarFlow_{i,t}}{TNA_{i,t-1}}$$

, which is interpreted as percentage net increase in fund asset due to investors purchase and redemptions. *Advantage, limitations and caveats of this measure are discussed in Chapter*

One of my dissertation.

Warther (1995) finds that flows are extremely slow-moving, probably due to the inertia of investors and the slow dispersion of information. When both concurrent flows and lagged flows are put into the same equation for explaining returns, the coefficient on concurrent flows are highly positively significant and the coefficient on lagged flows is negative. He argues that it may be the result of overreaction of investors or lagged flows serving as an instrument for concurrent flows. A further check reveals that the latter is the case. Thus Warther (1995) use an AR(3) model to orthogonize concurrent flows. To examine the decision of marginal investors, I adopt the same AR(3) model as Warther (1995). The monthly abnormal flow is defined as:

$$\mathrm{Flow}_{\mathrm{i,t}}^{a} = \mathrm{Flow}_{\mathrm{i,t}} - \sum_{k=t-3}^{t} \rho_{i,k} Flow_{i,k}$$

where $\rho_{i,k}$ is the autocorrelation coefficient of an AR(3) models. For robustness concerns, both abnormal flows and ordinary flows are used in the analysis.

3.3.1.2 Definitions of Performance

I measure performance of funds using either gross returns and abnormal returns (alphas), as past findings suggest both of them to be important determinants of flows. Sirri & Tufano (1998) and Ippolito (1992) find strong evidence that flows are correlated with past or concurrent abnormal returns. Warther (1995), Fant (1999), Ben-Rephael et al. (2012) find that flows are also associated with market and fund level returns. Abnormal return, commonly used by academics and practitioners, is a long-term risk-adjusted performance measure reflecting the manager's ability to outperform the market. Papers like Fama & French (2010) and KOSOWSKI et al. (2006) discuss the validity of abnormal return as a measure of manager skill. In contrast, gross return contains noise and do not account for risks inherent in the fund. However, gross returns may not be completely invalid in inferring fund prospect, mainly because of two facts. Firstly, past literature generally find persistence in *gross* fund returns, be it short or long term. Secondly, gross return may correlate with abnormal return, given the same level of risk. Thirdly, gross return has implications on tax burden of the fund, since it is the basis by which capital gain/losses are calculated.

For this purpose, Ivkovic & Weisbenner (2009) find evidence that investors respond to these two measure of performance differently. Inflows are influenced by ranks of return, a proxy for fund quality, while out flows are influenced by gross returns, the relevant benchmark for tax. The inclusion of gross return and abnormal return cover the primary concerns of the mutual fund investors, especially at the turn of the year: a desire to pick good manager and an aversion to tax burdens.

As abnormal return cannot be observed unless a lengthy sample is used, the abnormal returns are calculated as the alphas from a 12 month rolling regressions of fund return on factors. The factor models are either CAPM, Fama & French (1993) three factor model or a four factor model with the Carhart (1997) monthly momentum factor (MOM). For example, the four-factor rolling regression for fund i at month t measures the alpha as:

$$\mathrm{alpha}_{i,t} = R_{i,t} - R_f - \beta_{\mathrm{i,1}}(\mathrm{R_m} - \mathrm{R_f}) - \beta_{\mathrm{i,2}}\mathrm{SMB_t} - \beta_{i,3}HML_t - \beta_{i,4}\mathrm{MOM_t} - \epsilon_{\mathrm{i,t}}$$

where the factor loadings are computed using fund and factor returns from the past 12 months. These factor models are selected since Barber et al. (2016) and Berk & van Binsbergen (2016) document that fund investors attend to abnormal returns from all three factor models, with a elevated focus on CAPM. Another reason is that I must control for the established anomaly in finance, like the size, value and momentum effect. Even if investors do not specifically adjust for these additional risks, the factor loadings are likely to capture the fund styles, as previous papers find evidence on style-based return chasing Teo and Woo (2004); Frijns, Gilbert and Zwinkels (2016).

Gross returns are either one month return or 12 month returns. These two different horizons are used to disentangle the effect of long or short term returns on flows, especially at the turn of the year. Gross return has both an information effect and a tax burden effect. Both monthly and annual returns reveal the quality of the fund, despite the former is noisy and less accurate. However, gross return, especially long term, contain information on how much short term capital gain/losses the fund has accumulated during the year. When a fund has netted realized capital gains, the fund is required by the law to distribute most of the gains to pass though the tax to investors. Most funds do so before December 31st. Bergstresser & Poterba (2002) discuss this scenario and they find long-term return and turnover are strongly correlated with capital gain overhangs. In this regard, short term returns are less complicate by the tax effect and may be salient to investors at turn of the year.

The net effect of returns depends on relative strength of the tax burden effect or the information effect. For example, at December, a fund achieves a year-to-date return of 40%, but the monthly return is -5%. On the one hand, short term investors may worry about the short-term prospect of the fund and redeem shares in the fund accordingly. On the other hand, Long term investors may recognize the long-term prospect of the fund or are simply acquainted with the fund due to year end media exposures. However, for investors with special concerns on tax, this stellar performance signal huge unrealized short-term capital gains. The imminent fund distribution at year end not only accelerate redemptions from existing customers, but also hinder entrance of new investors.

Bollen (2007) warns that investors may simply chase return for no reason. Warther (1995) document correlation of flows to mainly concurrent returns and Goetzmann & Massa (2002) finds flows fully respond to returns within a week. Given these regularities and monthly frequency of this study, the sensitivity of flows to concurrent returns are treated as the object of interest. To control for potential return chasing and any residual information effect not captured by concurrent return, I also include lagged performance variables.

3.3.2 Piecewise Linear Regression Approach to Flow-performance Function

The shape of the flow-performance function can be measured by the slope on different performance level from a flow-performance regression. Past papers use different yet similar methodologies to measure this conditional effect. Sirri & Tufano (1998) regress flows on several dummies for ranked one-year gross return. Lynch & Musto (2003) regress flows on one-year gross returns as well. However, due to the limitation of the data, they are only able to allow a kink at zero. Ferreira et al. (2012) use high/medium/low dummies, but they also consider rank on abnormal returns, in addition to gross return.

In this study, a standard piecewise linear regression is used. The sheer size of our data allows more granulated decomposition of performance variables. In every month, funds are put into quintiles bases on their gross return and rolling alpha(s). The gross returns are either monthly or one-year returns, and the alphas are from CAPM, three factor and four factor regressions using data in the past 12 months. From lowest to highest quintile, five dummies, LOW, LOWM, MID, HIGHM and HIGH are constructed. These dummies are then made to interact with performance variables. Thus, this specification allows 4 kinks at the flow performance curve and the slope in every interval is quantitatively measured by the coefficient on the interactive terms. An OLS regression is run on the cross-section by months. To control for characteristics which previous studies show to influence flows, several control variables are added in the regression. The specification is:

$$\mathrm{Flow}_{\mathrm{i,t}} = \beta_0 + \beta_1 Flow_{t-1} + \beta_3 Perf_{i,t-1} + \psi_{0,t} Perf_{i,t} + \sum_{k=1}^{4} \psi_{k,t} Dummy_{i,k} Perf_{i,t} + \sum \beta \, Controls_{\mathrm{t-1}}$$

The term $Flow_{t-1}$ is to control for autocorrelation in flows and lagged performance (Perf) is to control for return chasing. $Perf_{i,t}$ is the concurrent performance variable and $\sum Dummy * Perf$ are interactive terms formed by multiplying dummies LOWM, MID, HIGHM and HIGH, with LOWM being the first dummy and HIGH being the fourth dummy. The coefficients ψ_0 to ψ_4 are the measure of the shape of flow-performance function. The absolute magnitude of the ψs measures sensitivities of flows to performances in every region at month t and the sign shows whether investors are momentum or contrarian. ψ_0

measures the slope at lowest quintile of performance because the effects of other quantiles are automatically accounted for by the four interactive terms. The ψ_1 to ψ_4 coefficients measure the slopes on other performance quintiles *relative to* the bottom quintiles, due to the nature of piecewise regression. For instance, ψ_1 measures the incremental slope on LOWM performance quintile relative to ψ_0. The true flow-performance sensitivity is thus $\psi_0 + \psi_1$. By this token, sensitivity of flows to top performers is $\psi_0 + \psi_4$. These slopes can be obtained for every month since it is a cross-sectional regression.

The control variables are the log of total net assets of the fund, risk of the fund and age of the fund in years. Papers that use (the logarithm of) TNA as controls are Patel et al. (1994), Sirri & Tufano (1998), Jain & Wu (2000), Cooper et al. (2005) and Huang et al. (2007). They generally find a negative relationship between size and flows. A negative relationship signals higher growth momentum of small funds or a reversion of investors for the diseconomy of scale of large funds. Risk of funds are computed as the lag of 12 month rolling standard deviation of fund returns. Ederington & Golubeva (2011) documents investors as risk averse: higher risk levels of both market and fund are associated with fun outflows. This is also consistent with asset pricing theory. Age of funds is the months elapsed since the official launch date of the fund divided by 12. Several papers find that investors react differently to the age of the fund. Chevalier & Ellison (1997) partition funds into young and old category and find flow-performance sensitivity to be higher for younger funds. In addition, the convexity of the function is weaker in younger funds. They argue it is because investors rely more on recent return of younger funds to learn its quality and they anticipate these funds to be more inclined to gamble later in the year. Huang et al. (2007) have a similar view.

3.3.3 Gross Flows Modelled by Propensity of Trade (PGR, PLR, PS)

To disentangle the effect from several competing hypothesis, we need to model inflows and outflows separately. As mentioned earlier, I do not have access to a micro data set that helps us calculate gross flows. Also, I do not have the luxury to track every fund share since it is a trillion-dollar business. Luckily, since we have longitudinal data of many funds, I can infer whether a certain group of funds has been purchased and sold in average. Thus I design several unique measure of investor's propensity for trade similar to methodologies found in Odean (1998) and Chang et al. (2016). These measures are called PGR (Proportion of Gains Realized), PLR (Proportion of Losses Realized) and PS (Probability of being Sold) These variables can be used as pseudo measures of gross flows.

Odean (1998) tries to measure the propensity of investors to redeem a fund when the fund experiences a loss or gain during some historical period. As disposition effect predict that investors are more likely to sold when facing a gain than a loss, they believe the propensity reveals whether investors suffer from disposition effect. Their measure is called PGR and PLR, the same names I am going to use in this study. The PGR is defined as the proportion of realized gains (as opposed to paper gains) among total capital gains. The PLR is similar but defined by realized losses. The Chang et al. (2016) version to solve the same problem is to use dummy variables and regression. They regress a dummy of sale (1 for asset sold and 0 for asset not sold) on whether the investment has gained in value.

PGR in this study is defined as:

$$\mathrm{PGR_t} = \frac{\text{Number of funds with outflows and positive returns}_{\mathrm{t-k}}^{\mathrm{t}}}{\text{Number of funds with positive returns}_{\mathrm{t-k}}^{\mathrm{t}}}$$

And PLR is defined as

$$\mathrm{PLR_t} = \frac{\text{Number of funds with outflows and negative return}_{\mathrm{t-k}}^{\mathrm{t}}}{\text{Number of funds with negative returns}_{\mathrm{t-k}}^{\mathrm{t}}}$$

where flows are calculated as in 3.3.1.1 and returns can be any measures that defined in 3.3.1.2. t is month and k is the time elapsed since beginning of the year. PGR measures the proportion of funds experiencing outflows when these funds are performing better than average. As flows and returns are all relative to k, PGR will also be relative to k. PGR with k=10 with return defined as gross year-to-date return measures the percentage of funds with negative flows from January to October among funds with positive gross returns from January to October. In October, if there are 500 funds with positive year-to-date return and there are 300 funds in these 500 funds with negative flows, PGR in October will be 0.6. The definition of PLR is exactly the opposite.

The purpose of PGR and PLR is to replicates the behaviour of gross flows using the rich information in cross-section and they can be used to test hypothesis from several theories. For example, tax-loss selling predicts lower PGR near the end of the year while having no specific predictions on the sensitivity of net flows on returns. As funds accumulate gains during the year, investors are less likely to sell the fund since they may have unrealized capital gains. They will wait until the capital gains becomes long-term. By the same token, PLR should be higher throughout the year as investors harvest funds with capital-losses. Portfolio rebalance as opposite predictions. PGR should be higher near end of the year as investors sell winning funds to restore their initial weight. PLR should be lower near year end as investors buy into losing funds. As long as there are consistently large number of funds in sample, PGR and PLR will converge to true proportions calculated by real gross flows.

Tax-loss selling and portfolio rebalance not only predict the *existence* of alternation in flow-performance relationship – but also the magnitude and dispersion of it. It is reasonable that extreme performance will invoke more course of actions of investors than intermediate returns. For example, top 10 funds in terms of gross return at end of year will have much more tax bearings to investors than top 100 funds. From the perspective of portfolio rebalance, top 10 funds will deviate more substantially from original weight at end of year than top 100 funds. Same logics apply to bad performers. I expect that funds at extreme performance quintiles will have larger propensity of being traded than intermediate quintiles. Simple regressions and PGR/PLR will not reveal these structures. To measure the propensity of a certain performance quintile being sold, I design the PS (probability of being sold) measure. PS is calculated as:

$$\mathrm{PS}_{\mathrm{t}}^{\mathrm{k}} = \frac{\text{Number of funds with outflows in quintile } \mathrm{k_t}}{\text{Number of funds in quintile } \mathrm{k_t}}$$

k stands for quintile of any performance defined in 3.1.2. and the numerator is the number of funds with outflows as for time t among quintile k. For example, at October, there are 100 funds at quintile 5 ranked by year-to-date return, among which 30 funds experience outflow during January to October. Thus, $\mathrm{PS}_{t=10}^{k=5}$=30/100=0.3. PS reveals the dispersion in *change* in flow-performance relationship. Like PGR and PLR, it is a pseudo measure of gross flows.

3.4 Data

The primary dataset used in this study is from Thomson Reuters Datastream. Datastream has a comprehensive list for all active U.S mutual funds. In addition, there is coverage for merged and dead funds. These data contain monthly market price, total expense ratio, total net assets and qualitative variables for funds. Our sample starts from 31/12/1998 to 31/06/2017. I select domestic open-end equity mutual funds from Lipper Global Objective: Only funds labelled “Equity US”, “Equity US Income” and “Equity US Small And Mid-Cap” are included. To make sure the funds is only available to domestic investors, I drop funds that aim for foreign investors and funds not denominated in US Dollar. Because fund with very little assets under management are probably not generally available to the public (the so called incubated funds), I follow Franzoni and Schmalz (2017) set the minimal latest total net assets to be above 5,000,000 US Dollars. To ensure enough observations are available for analysis, I exclude funds with less than 12 months of price history. The filter scheme leaves us around 3,500 mutual funds and 250 ETFs. Other data I obtained includes information on whether a fund is a mutual fund or index fund, or whether a fund is a pension fund, whether a fund has a 12b1 expense on income statement and the launch date of the fund. The 12b1 expense and launch date is obtained from Morningstar, a leading data provider for global mutual funds. However, only the most recent data is available in our subscription. The 12b1 expense, as used in many studies (for example Sirri and Tufano 1998; Barber, Odean and Zheng 2005) before, proxies for the advertisement activities of mutual funds. The launch dates are to obtain the age of the funds, which are shown in some papers (for example Huang, Wei and Yan 2012) to be one of the determining factors in consumers evaluation process.

Table 3-1 Descriptive Statistics for Mutual Fund Characteristics

	Mean	Min	Max	Median	Std.	# of funds
Total Net Assets	1279.67	5	146311.50	248.15	5639.50	3516
Price	24.76	1.42	832.63	18.47	30.30	3516
Total Net Expense	1.00	0.00	2.50	0.98	0.44	3446
Age	14.05	1.23	85.75	13.25	10.69	3516
12b1 Fee	0.43	0.00	1.00	0.25	0.33	1465

The table shows descriptive statistics for fund characteristics, measured as of 31/12/2015. Total Net Asset are from financial reports published by Thomson Reuters. Price is the official close price. Total Net Expense is net of waivers/reimbursements, but before expense offsets/brokerage service arrangements. TERs are as reported in the financial highlights in the annual report. Age is the difference between current year and year first appeared in Datastream. 12-b1 fees are as reported in the annual report.

Table 3-1 reports the summery statistics for mutual fund characteristics, as of December 2015. The mean total net assets are 1280 million and the median is 248 million, suggesting a skewed distribution to the small funds. The age of the funds ranges from 1.23 years to 85 years, suggesting coexistence of young and old funds. The mean age of the funds is moderately 14 years. From the TER and 12-b1 fee data, it is surprising that funds devote a substantial amount of fees collected from investors to advertise themselves. The mean Total Net Expense is 1 percent per year and mean 12b1 fee, 0.43, takes nearly a half, though it is cautioned that only 1,465 funds report a 12-b1 fee.

To visualize the sample size I have, I aggregate the TNA for all mutual funds in sample. As shown in Figure 3-1, at the start of the sample, 1,000 billion dollars of assets are in our sample. The fluctuations of the AUMs during the sample match anecdotal impressions of US market. This suggest that 1. Our dataset is a representative sample overall and 2. Fund investors actions are highly related to the market. At the end of the sample I have nearly 5,000 billion of available assets.

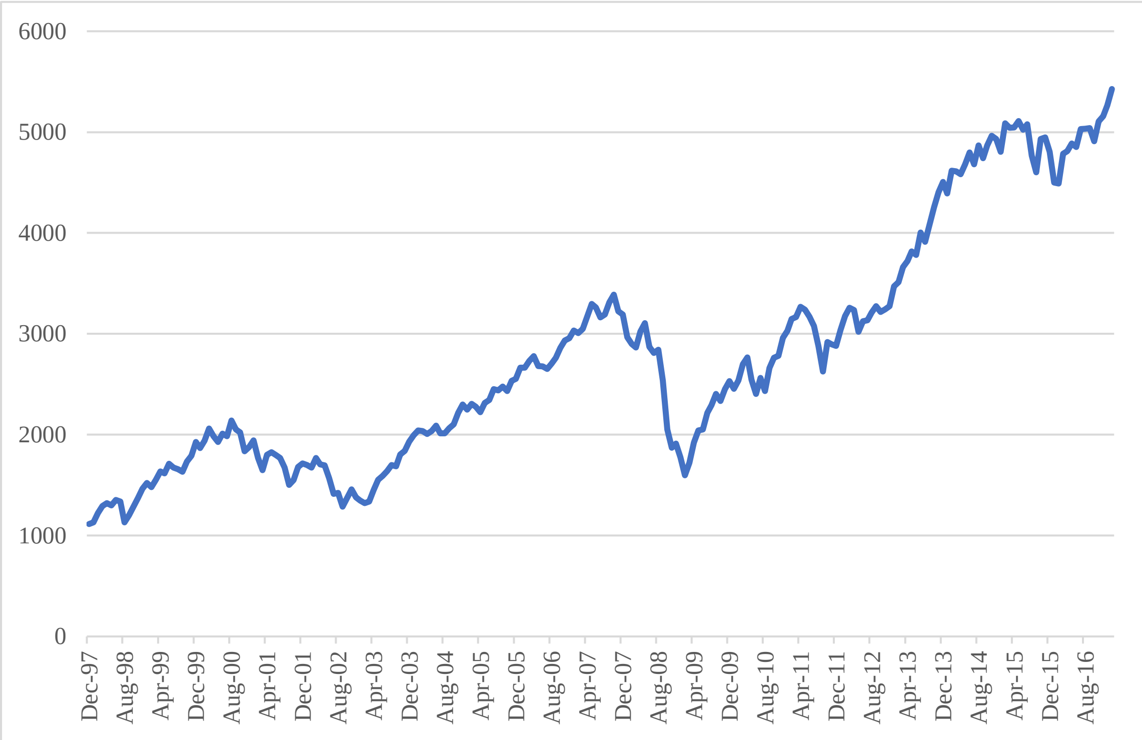


Figure 3-1 Time Series of Aggregate Sample TNA

To have a preliminary understanding of the seasonality of data, I summarize the one-month flow and return variables for mutual funds in Table 3-2. To avoid influence from outliers, flows and returns are trimmed at 0.5% and 99.5% level. The mean fund flows are fairly stable throughout the year, except December. At January to November, there are generally 1% of net inflows. December saw a surge in inflows, which is 4%. This is explained by the re-investment of dividends, year-end bonuses or the joint investments of individuals who concentrate their actions at year end. The pattern of flows is consistent with the rebalance hypothesis, instead of tax-loss hypothesis, which predicts a net outflow at year end. Median flows and positive skewness suggest that the positive mean flows are brought about by large inflows. Financial theory does not have a clear implication for fund returns across year, which is reflected in the one month return statistics. The mean flows are irregular in the year. March and October are months with highest fund returns, while January and December saw lowest returns. During the whole sample period, mean flow and returns are all positive.

Table 3-2 Descriptive Statistics of 1 Month Flow and Return Variables

	1 Month Flows				1 Month Returns			
Month	mean	p50	sd	skewness	mean	p50	sd	skewness
1	0.0154	0.0002	0.0641	3.2292	-0.0067	-0.0112	0.0461	-0.0578
2	0.0126	0.0000	0.0564	3.6404	0.0103	0.0163	0.0427	-1.0090
3	0.0142	0.0008	0.0600	3.3915	0.0223	0.0181	0.0372	-0.1025
4	0.0149	0.0011	0.0589	3.5729	0.0139	0.0102	0.0370	0.2441
5	0.0122	-0.0004	0.0560	3.9001	0.0044	0.0143	0.0425	-0.5608
6	0.0128	0.0006	0.0552	3.7991	-0.0062	-0.0044	0.0365	-0.4653
7	0.0109	-0.0012	0.0571	3.7213	0.0063	0.0030	0.0460	-0.1678
8	0.0105	-0.0015	0.0555	3.7782	-0.0046	0.0036	0.0410	-0.4586
9	0.0099	-0.0011	0.0540	3.9421	-0.0056	0.0032	0.0556	-0.3181
10	0.0115	-0.0012	0.0582	3.6585	0.0221	0.0271	0.0428	-0.3231
11	0.0133	-0.0006	0.0587	3.5924	0.0141	0.0205	0.0444	-1.0037
12	0.0416	0.0244	0.0707	2.1139	-0.0106	-0.0029	0.0511	-0.4302
1 to 12	0.0150	0.0005	0.0595	3.4076	0.0048	0.0092	0.0453	-0.4584

Flows and Returns are winsorized at 1% level.

Table 3-3 Descriptive Statistics for Rolling Fund Factor Loadings

	Variable	Mean	Median	Sd	Skewness
Carhart (1997) Four-Factor Model	Beta	0.966	0.980	0.266	-0.262
	Beta_SMB	0.166	0.083	0.432	0.492
	Beta_HML	-0.091	-0.053	0.622	-0.302
	Beta_MOM	0.006	0.000	0.319	0.219
	Alpha	-0.003	-0.002	0.007	-0.395
Three-Factor Model	Beta	0.986	0.995	0.224	-0.370
	Beta_SMB	0.179	0.098	0.433	0.504
	Beta_HML	-0.064	-0.027	0.485	-0.517
	Alpha	-0.003	-0.002	0.007	-0.473
CAPM	Beta	1.030	1.011	0.230	0.309
	Alpha	-0.002	-0.002	0.007	-0.002

Monthly factor data is from website of K. French (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html). All loadings on factors are calculated using rolling OLS regressions (trailing 12 months). Fund returns are winsorized at 1% level.

Table 3-3 summarize rolling factor loadings for all mutual funds. The observations in the table are pooled for every month in the sample. The loadings are obtained from Carhart (1997) four factor model, Fama and French (1993) three factor model and CAPM. To avoid influence from extreme values, all loadings are trimmed at 1% level. During the sample period, mutual funds generally yield negative Alphas, measured by either of the four models. Other factors show that the sample funds are slightly preferring small, low book-to-market value stocks and choosing a momentum investment style. Betas are around one, suggesting the market neutrality of the aggregate fund portfolios.

3.5 Empirical Findings

3.5.1 Empirical Flow-Alpha Function

When performance is measured in a risk adjusted way, intercept from factors models is an accessible proxy. In this section, I use our sample data to show the relationship between flows and alphas. However, the selection of asset pricing models complicates the matter. It is unclear which model investors are actually using to adjust for risk. At the very least, the validity of each factor model is still debatable. Barber, Huang and Odean (2016) and Berk and van Binsbergen (2016) are two papers that specialize in this issue. The former is a test on pricing models and the latter aim to find which factor investors attend to most. As the purpose of our study is none of the above, I do not dive into philosophical debates here. The aim is to examine if there is any flow-performance relationship and their shapes conditional or unconditional on the calendar months. However, as a cautionary measure, I include the four, three and one factor model which are shown to be useful in explaining the cross-section of stock returns.

Table 3-4 shows the result for flow-performance relationship using CAPM alphas, while the flows are one-month flows. I regress flows on several variables shown to be relevant in Section 3.3.2. Unlike previous studies, the regressions are done by month, instead of using whole sample. The bottom row computes the average of regression coefficients across months. I confirm a classical convex flow-performance relationship from the bottom row. The average coefficient on the contemporaneous alpha is 0.068, meaning that the flows are in the same direction of the alphas. This implies that the funds with worst risk adjusted performances are punished by investors. By the definition of piecewise linear regression, the sensitivities of flows to the other alpha quintiles are the sum of coefficients on the respective interactive terms and the basic coefficient. Thus, sensitivities to the second, third, fourth and fifth alpha quintiles are -0.01, -0.122, -0.058 and 0.479 respectively. There is a very strong positive response to the top performing funds, and a muted response to the medium quintiles. This result is explained in Berk and Green (2004) and Huang, Wei and Yan (2012) where investors are depicted as Bayesian and fund flows are competitive. In addition, Sirri and Tufano (1998) attributes this convexity to search cost. Coefficient on past flows are 0.388, suggesting a highly autocorrelated structure, which is already discovered in Warther (1995). Coefficient on CAPM alpha is 0.668, showing a general scenario where flows has a persistent preference for past good performers. Besides, result from the controlling variables shows a slight aversion to large size, aversion to risk and no effect from age. Berk and Green (2004) argue that large size signal future diseconomy of scale. Ederington and Golubeva (2011) documents that risk and flows are negatively correlated.

The other rows in Table 3-4 shows these relationships by months, which are one of the main contributions of the study. I control for individual effect using fixed effect model, pooling data for each month for the whole sample. This methodology intentionally release constraint on individual effects. The benefits of doing so is that the structural change in coefficients are captured. The results show that the relationship change significantly throughout the year. The most intriguing phenomenon I identify is a strong contrarian behaviour towards low alpha funds in month of December, as shown in coefficients for the piecewise regression per month. To visualize the structural shift, I draw the sensitivities of flows to alpha of each quintiles against the calendar months in Figure 3-2.

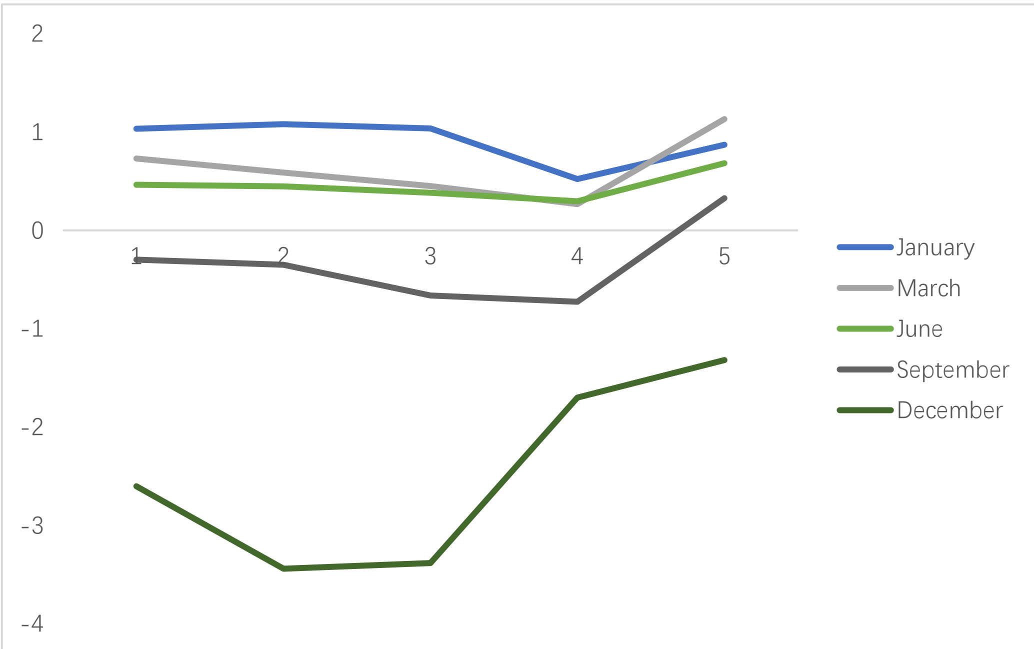


Figure 3-2 Sensitivities of One-Month Flows to CAPM-Alpha Deciles Across Year

For top alpha decile funds, the sensitivities of flows to the performance of these group are generally positive across the year, with a sensitivity coefficient ranging from 0.5 to 1. The highest sensitivity occurs on December, which is consistent with the established fact that year-end rankings are very salient to return chasing consumers. In January, March, June and September, the flows are positively related to all alpha deciles except for some cases, suggesting a classic rewarding and punishing mechanism in competitive fund market. However, it is counterintuitive that in December, the lagging funds are not punished as occurred in the normal months. Investors are contrarian to the bottom, fourth and third quintiles: flows escape from better funds to worse funds in these groups. This would not have been discovered had I used the whole sample. The coefficient on risk(t-1) in December is also vastly different from other months. Investors transform from risk adverse to risk seeking, and the latter is economically significant. In December, When the annualized standard deviation of the funds during the past 12 months are higher by 1%, it is translated into 0.52% of inflows. In fact, the absence of risk aversion has already started in November. The year-end shift in risk aversion has never been documented before.

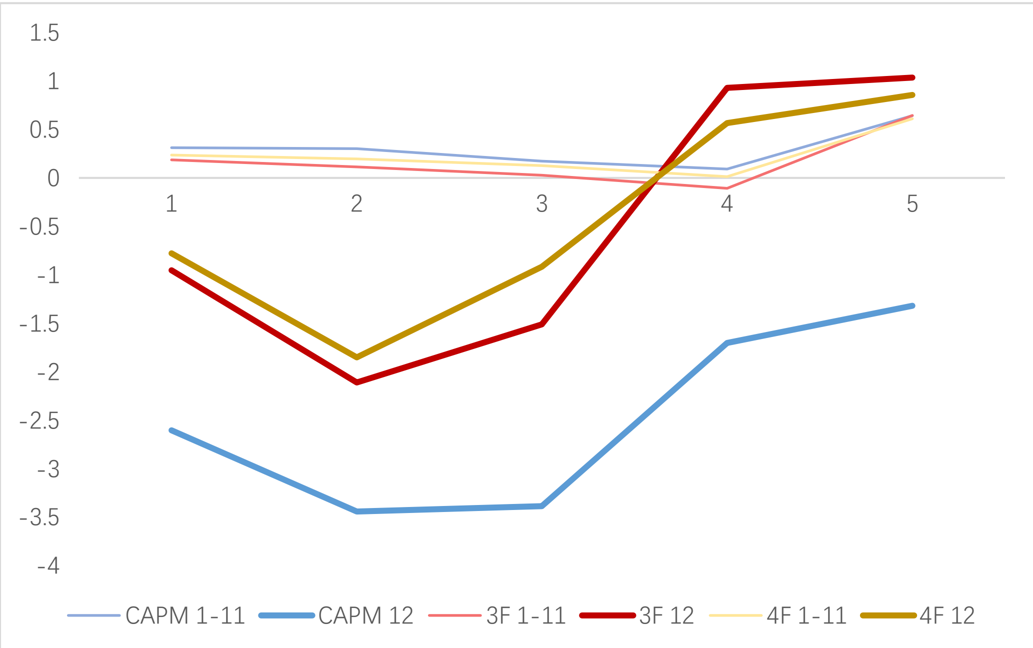


Figure 3-3 Flow-Performance Function Across Year Using CAPM, Three-Factor and Four-Factor Alphas

Table 3-4 Flow-Performance Regression by Month Using Rolling CAPM Alpha

Month	Flow(t-1)	Alpha(t-1)	Alpha(t)	LOWM *Alpha(t)	MID *Alpha(t)	HIGHM* Alpha(t)	HIGH *Alpha(t)	LogTNA (t-1)	Risk(t-1)	Age(t-1)	Constant	Obs.	F	Adj.R2
1	0.331	0.800	1.035	0.045	0.001	-0.513	-0.164	-0.003	-0.285	0.000	0.037	37758	437.70	20.96%
	(41.29)	(7.85)	(9.00)	(0.51)	(0.01)	(-3.54)	(-1.32)	(-18.15)	(-20.95)	(-19.96)	(31.02)			
2	0.382	-0.079	0.736	0.013	-0.588	-0.387	0.228	-0.001	-0.049	0.000	0.018	35124	401.91	26.37%
	(39.33)	(-0.97)	(8.12)	(0.19)	(-5.91)	(-3.07)	(2.11)	(-9.85)	(-4.59)	(-14.97)	(17.52)			
3	0.462	0.016	0.730	-0.144	-0.280	-0.463	0.402	-0.002	-0.078	0.000	0.022	35999	416.44	26.51%
	(35.43)	(0.18)	(7.35)	(-2.05)	(-2.57)	(-3.42)	(3.18)	(-10.60)	(-8.45)	(-16.39)	(20.35)			
4	0.404	0.368	0.503	-0.036	0.019	-0.139	0.415	-0.002	0.035	0.000	0.023	35392	421.32	25.03%
	(33.94)	(3.45)	(4.53)	(-0.44)	(0.17)	(-1.14)	(3.49)	(-14.99)	(3.21)	(-13.16)	(20.65)			
5	0.368	0.501	0.275	-0.048	-0.124	0.098	0.280	-0.002	-0.092	0.000	0.021	35748	369.27	23.37%
	(32.66)	(4.70)	(2.57)	(-0.67)	(-1.13)	(0.74)	(2.54)	(-12.65)	(-8.35)	(-12.53)	(20.29)			
6	0.398	0.124	0.465	-0.017	-0.084	-0.169	0.218	-0.002	-0.047	0.000	0.021	35932	310.60	20.23%
	(32.94)	(1.11)	(4.02)	(-0.21)	(-0.75)	(-1.30)	(1.91)	(-12.30)	(-3.98)	(-12.28)	(19.74)			
7	0.379	0.394	0.360	0.105	-0.237	-0.105	0.309	-0.002	-0.069	0.000	0.022	37228	325.85	19.51%
	(30.61)	(4.14)	(3.60)	(1.44)	(-2.01)	(-0.85)	(2.65)	(-13.35)	(-6.12)	(-17.06)	(20.85)			
8	0.380	0.441	0.314	-0.053	0.091	0.083	0.603	-0.002	-0.058	0.000	0.020	37575	386.44	22.77%
	(33.53)	(4.59)	(3.02)	(-0.71)	(0.82)	(0.66)	(5.18)	(-12.51)	(-4.79)	(-14.47)	(18.60)			
9	0.374	0.987	-0.297	-0.054	-0.364	-0.429	0.624	-0.001	-0.070	0.000	0.018	37067	343.26	21.26%
	(30.47)	(9.52)	(-2.90)	(-0.84)	(-3.41)	(-3.42)	(5.15)	(-9.21)	(-6.04)	(-17.33)	(17.33)			
10	0.421	0.579	0.248	0.049	0.053	-0.163	0.556	-0.002	-0.012	0.000	0.022	34103	385.40	22.81%
	(29.35)	(5.27)	(2.04)	(0.61)	(0.44)	(-1.24)	(4.61)	(-13.45)	(-1.44)	(-15.81)	(20.39)			
11	0.371	1.845	-0.953	0.043	0.016	-0.221	0.172	-0.002	0.054	0.000	0.019	34004	357.02	21.77%
	(31.62)	(13.07)	(-6.77)	(0.53)	(0.14)	(-1.73)	(1.58)	(-11.52)	(5.53)	(-13.99)	(17.06)			
12	0.381	2.038	-2.602	-0.839	-0.783	0.900	1.283	-0.002	0.547	0.000	0.015	33584	532.68	20.56%
	(30.45)	(23.89)	(-24.79)	(-7.62)	(-5.31)	(4.90)	(8.24)	(-9.04)	(41.63)	(-8.86)	(12.25)			
12M Avg.	0.388	0.668	0.068	-0.078	-0.190	-0.126	0.411	-0.002	-0.010	0.000	0.021			

The table shows pairwise OLS regression of monthly fund flows on performances defined by rolling CAPM Alpha. The LOWM, MID, HIGHM, HIGH in interaction terms stand for quintile 2, 3, 4, 5 of rolling CAPM alphas of sample funds. Regressions are run on cross-section of funds every month. Risk is trailing 12 months standard deviation of fund returns. Flows and risk variables are winsorized at 1% level. Last row is arithmetic average of coefficients from regressions for all months. Robust t-stat is reported in parenthesis.

Table 3-5 Flow-Performance Regression by Month Using Rolling Fama French Three-Factor Alpha

Month	Flow(t-1)	Alpha(t-1)	Alpha(t)	LOWM *Alpha(t)	MID *Alpha(t)	HIGHM* Alpha(t)	HIGH *Alpha(t)	LogTNA (t-1)	Risk(t-1)	Age(t-1)	Constant	Obs.	F	Adj.R2
1	0.328	1.234	0.059	0.279	0.018	-0.936	0.198	-0.003	-0.304	0.000	0.038	37772	366.08	19.10%
	(40.16)	(11.84)	(0.54)	(3.64)	(0.16)	(-5.69)	(1.36)	(-19.40)	(-21.31)	(-20.65)	(31.81)			
2	0.391	0.062	0.376	-0.174	-0.209	-0.439	0.428	-0.001	-0.060	0.000	0.017	35215	368.73	26.08%
	(40.54)	(0.74)	(4.31)	(-2.91)	(-2.26)	(-3.73)	(3.71)	(-9.86)	(-5.36)	(-14.90)	(17.29)			
3	0.476	0.131	0.461	-0.255	-0.347	-0.641	0.579	-0.002	-0.080	0.000	0.021	35990	384.28	26.37%
	(36.74)	(1.48)	(5.03)	(-4.32)	(-3.81)	(-5.98)	(4.54)	(-10.57)	(-8.60)	(-15.94)	(19.58)			
4	0.421	0.572	0.023	-0.112	-0.107	-0.129	0.619	-0.002	0.031	0.000	0.022	35173	347.24	24.73%
	(35.57)	(6.47)	(0.26)	(-1.64)	(-1.19)	(-0.97)	(5.01)	(-14.53)	(2.75)	(-13.39)	(19.61)			
5	0.379	0.400	0.056	-0.136	-0.069	0.105	0.540	-0.002	-0.071	0.000	0.019	35513	294.13	22.83%
	(34.21)	(5.25)	(0.70)	(-2.19)	(-0.83)	(0.97)	(4.53)	(-12.12)	(-6.32)	(-13.12)	(18.47)			
6	0.400	0.229	0.223	-0.018	-0.120	-0.247	0.399	-0.002	-0.040	0.000	0.020	35724	276.37	19.82%
	(33.75)	(2.53)	(2.29)	(-0.27)	(-1.37)	(-2.14)	(3.11)	(-11.70)	(-3.41)	(-12.51)	(18.74)			
7	0.384	0.465	0.215	-0.140	-0.203	-0.044	0.267	-0.002	-0.076	0.000	0.022	36876	292.84	19.06%
	(31.03)	(5.70)	(2.72)	(-1.97)	(-2.32)	(-0.33)	(2.18)	(-13.13)	(-6.70)	(-17.65)	(20.79)			
8	0.385	-0.080	0.793	-0.090	-0.293	-0.133	0.192	-0.002	-0.079	0.000	0.022	37317	344.82	22.00%
	(33.95)	(-0.91)	(7.81)	(-1.32)	(-2.78)	(-0.98)	(1.53)	(-13.08)	(-6.48)	(-15.41)	(20.10)			
9	0.379	0.582	0.027	-0.121	-0.326	-0.466	0.402	-0.001	-0.070	0.000	0.018	37141	315.44	20.47%
	(31.22)	(6.60)	(0.30)	(-1.83)	(-3.30)	(-4.02)	(3.49)	(-9.47)	(-6.07)	(-17.57)	(17.66)			
10	0.428	0.529	0.162	0.022	-0.100	-0.276	0.658	-0.002	0.000	0.000	0.022	34239	347.77	21.96%
	(30.07)	(6.03)	(1.72)	(0.30)	(-0.98)	(-1.87)	(4.99)	(-13.52)	(0.01)	(-16.65)	(20.25)			
11	0.378	1.071	-0.360	-0.048	0.026	-0.009	0.770	-0.002	0.071	0.000	0.017	34093	334.80	21.93%
	(32.56)	(7.85)	(-2.46)	(-0.59)	(0.25)	(-0.06)	(5.72)	(-10.77)	(7.32)	(-14.53)	(15.56)			
12	0.383	0.256	-0.954	-1.156	-0.558	1.883	1.989	-0.002	0.548	0.000	0.014	33689	458.52	19.51%
	(30.95)	(4.11)	(-11.01)	(-10.77)	(-3.63)	(9.62)	(12.78)	(-8.08)	(41.45)	(-10.21)	(11.13)			
12M Avg.	0.394	0.454	0.090	-0.162	-0.191	-0.111	0.587	-0.002	-0.011	0.000	0.021			

The table shows pairwise OLS regression of monthly fund flows on performances defined by rolling Fama French Three-Factor Alpha. The LOWM, MID, HIGHM, HIGH in interaction terms stand for quintile 2, 3, 4, 5 of rolling Three-Factor Alphas of sample funds. Regressions are run on cross-section of funds every month. Risk is trailing 12 months standard deviation of fund returns. Flows and risk variables are winsorized at 1% level. Last row is arithmetic average of coefficients from regressions for all months. Robust t-stat is reported in parenthesis.

Table 3-6 Flow-Performance Regression by Month Using Rolling Fama French Four-Factor Alpha

Month	Flow(t-1)	Alpha(t-1)	Alpha(t)	LOWM *Alpha(t)	MID *Alpha(t)	HIGHM* Alpha(t)	HIGH *Alpha(t)	LogTNA (t-1)	Risk(t-1)	Age(t-1)	Constant	Obs.	F	Adj.R2
1	0.328	0.609	0.567	0.338	0.104	-0.451	0.107	-0.003	-0.298	0.000	0.037	37833	357.0811	0.1872389
	(40.48)	(6.94)	(5.68)	(4.16)	(0.89)	(-3.10)	(0.83)	(-19.19)	(-21.06)	(-20.64)	(31.13)			
2	0.391	-0.028	0.415	-0.173	-0.292	-0.244	0.213	-0.001	-0.066	0.000	0.017	35229	355.0429	0.2578824
	(40.63)	(-0.32)	(4.66)	(-2.69)	(-3.02)	(-2.22)	(2.11)	(-9.91)	(-5.81)	(-14.87)	(17.32)			
3	0.479	0.316	0.213	-0.241	-0.307	-0.740	0.392	-0.002	-0.081	0.000	0.021	36020	367.523	0.2617717
	(37.05)	(4.23)	(2.69)	(-3.97)	(-3.32)	(-7.12)	(3.37)	(-10.76)	(-8.79)	(-16.18)	(19.57)			
4	0.425	0.318	0.210	-0.056	-0.051	-0.025	0.306	-0.002	0.030	0.000	0.021	35169	332.6365	0.2439654
	(35.99)	(4.41)	(2.95)	(-0.86)	(-0.59)	(-0.20)	(2.76)	(-14.49)	(2.68)	(-13.61)	(19.48)			
5	0.384	0.495	-0.101	-0.165	-0.148	0.002	0.367	-0.002	-0.060	0.000	0.019	35501	283.0843	0.2269382
	(34.55)	(6.39)	(-1.23)	(-2.69)	(-1.79)	(0.02)	(3.53)	(-12.14)	(-5.42)	(-13.80)	(18.28)			
6	0.403	0.163	0.247	0.022	-0.090	0.072	0.238	-0.002	-0.042	0.000	0.020	35631	265.218	0.1971941
	(33.74)	(2.36)	(3.19)	(0.35)	(-1.04)	(0.51)	(2.02)	(-11.63)	(-3.64)	(-12.33)	(18.68)			
7	0.392	0.285	0.214	-0.001	-0.152	-0.063	0.424	-0.002	-0.081	0.000	0.022	36835	284.2869	0.1911969
	(31.60)	(3.50)	(2.61)	(-0.02)	(-1.81)	(-0.58)	(3.48)	(-12.94)	(-7.12)	(-17.85)	(20.36)			
8	0.391	0.127	0.504	-0.080	-0.158	-0.302	0.211	-0.002	-0.089	0.000	0.022	37240	336.7441	0.2220662
	(34.47)	(1.74)	(5.98)	(-1.22)	(-1.59)	(-2.72)	(1.75)	(-12.92)	(-7.27)	(-15.34)	(20.20)			
9	0.389	0.290	0.259	-0.089	-0.169	-0.423	0.325	-0.001	-0.083	0.000	0.019	37083	302.5027	0.2072935
	(31.49)	(4.16)	(3.52)	(-1.37)	(-1.64)	(-3.65)	(2.70)	(-9.21)	(-7.10)	(-17.34)	(17.68)			
10	0.432	0.645	-0.031	0.078	-0.030	-0.379	0.720	-0.002	0.002	0.000	0.022	34184	336.9002	0.2223786
	(30.40)	(8.30)	(-0.37)	(1.04)	(-0.27)	(-2.89)	(5.64)	(-13.51)	(0.19)	(-16.74)	(20.09)			
11	0.385	0.457	0.109	-0.065	0.066	0.094	0.803	-0.002	0.076	0.000	0.016	34029	305.2487	0.2162492
	(33.15)	(3.97)	(0.89)	(-0.78)	(0.62)	(0.64)	(6.14)	(-10.40)	(7.78)	(-14.90)	(14.25)			
12	0.384	0.283	-0.777	-1.074	-0.141	1.342	1.633	-0.002	0.567	0.000	0.015	33642	433.8325	0.1909143
	(30.85)	(4.73)	(-8.86)	(-9.63)	(-0.88)	(7.29)	(10.91)	(-8.35)	(42.35)	(-9.82)	(11.47)			
12M Avg.	0.399	0.330	0.152	-0.126	-0.114	-0.093	0.478	-0.002	-0.010	0.000	0.021			

The table shows pairwise OLS regression of monthly fund flows on performances defined by rolling Fama French Four-Factor Alpha. The LOWM, MID, HIGHM, HIGH in interaction terms stand for quintile 2, 3, 4, 5 of rolling Four-Factor Alphas of sample funds. Regressions are run on cross-section of funds every month. Risk is trailing 12 months standard deviation of fund returns. Flows and risk variables are winsorized at 1% level. Last row is arithmetic average of coefficients from regressions for all months. Robust t-stat is reported in parenthesis.

Table 3-7 Flow-Performance Regression by Month Using 12-Month Returns

Month	Flow(t-1)	Return (t-1)	Return(t)	LOWM *Return(t)	MID *Return(t)	HIGHM* Return(t)	HIGH *Return(t)	LogTNA (t-1)	Risk(t-1)	Age(t-1)	Constant	Obs.	F	Adj.R2
1	0.325	-0.012	0.040	-0.017	-0.011	-0.004	0.030	-0.004	-0.274	0.000	0.034	38251	357.6155	0.1825088
	(40.37)	(-2.87)	(7.93)	(-4.01)	(-2.56)	(-0.82)	(6.92)	(-20.07)	(-18.51)	(-23.04)	(26.90)			
2	0.388	0.042	-0.011	-0.014	-0.021	-0.013	0.003	-0.002	-0.031	0.000	0.016	33935	348.3834	0.2674066
	(39.60)	(8.42)	(-2.38)	(-4.46)	(-5.93)	(-3.99)	(0.90)	(-10.58)	(-2.99)	(-15.09)	(15.90)			
3	0.479	-0.053	0.087	-0.029	-0.025	-0.018	-0.002	-0.002	-0.075	0.000	0.021	35107	360.4975	0.2679691
	(36.32)	(-10.06)	(14.61)	(-7.42)	(-6.29)	(-4.75)	(-0.48)	(-11.00)	(-6.73)	(-16.28)	(18.49)			
4	0.413	-0.024	0.061	-0.015	-0.014	-0.011	0.011	-0.003	0.153	0.000	0.017	35334	327.7587	0.2397122
	(34.65)	(-5.44)	(10.57)	(-4.15)	(-3.21)	(-2.58)	(2.32)	(-15.19)	(10.32)	(-14.36)	(14.55)			
5	0.387	-0.019	0.039	-0.023	-0.022	-0.026	0.002	-0.002	0.013	0.000	0.016	36849	269.8502	0.2238995
	(35.37)	(-5.71)	(9.02)	(-6.01)	(-5.32)	(-6.81)	(0.55)	(-11.98)	(0.99)	(-14.60)	(15.47)			
6	0.400	0.002	0.015	-0.010	-0.007	-0.008	0.011	-0.002	0.005	0.000	0.017	37178	260.4266	0.193893
	(34.17)	(0.53)	(3.14)	(-2.73)	(-1.64)	(-1.89)	(2.86)	(-11.86)	(0.46)	(-13.47)	(16.60)			
7	0.385	-0.026	0.066	-0.017	-0.024	-0.013	0.015	-0.002	-0.042	0.000	0.019	38456	319.2004	0.2020518
	(32.14)	(-7.73)	(14.75)	(-3.92)	(-5.63)	(-2.85)	(3.19)	(-14.14)	(-3.65)	(-18.70)	(18.41)			
8	0.390	0.007	0.012	-0.024	-0.019	-0.016	0.016	-0.002	-0.070	0.000	0.020	38643	312.258	0.2136397
	(35.01)	(2.10)	(2.87)	(-5.74)	(-4.35)	(-3.68)	(3.68)	(-13.22)	(-5.40)	(-17.27)	(18.49)			
9	0.383	0.015	0.011	-0.013	-0.009	-0.005	0.021	-0.002	-0.030	0.000	0.016	38096	297.3591	0.2064136
	(32.47)	(6.00)	(3.48)	(-3.32)	(-2.28)	(-1.41)	(5.15)	(-10.59)	(-2.52)	(-17.72)	(14.80)			
10	0.424	0.014	0.015	-0.017	-0.005	0.005	0.024	-0.002	0.031	0.000	0.017	35059	330.7298	0.2180732
	(30.42)	(4.57)	(3.44)	(-3.19)	(-0.91)	(0.90)	(4.92)	(-13.33)	(3.10)	(-18.82)	(15.37)			
11	0.387	0.042	0.003	-0.034	-0.030	-0.022	-0.011	-0.002	0.119	0.000	0.013	34876	305.7637	0.208676
	(32.86)	(10.39)	(0.47)	(-6.32)	(-5.61)	(-4.31)	(-2.13)	(-11.78)	(10.83)	(-15.59)	(11.93)			
12	0.374	0.147	-0.087	-0.010	-0.022	-0.042	-0.034	-0.002	0.636	0.000	0.016	34522	542.3715	0.2031167
	(30.35)	(28.04)	(-12.40)	(-1.58)	(-3.48)	(-6.88)	(-5.76)	(-10.13)	(45.35)	(-8.89)	(11.38)			
12M Avg.	0.394	0.011	0.021	-0.019	-0.017	-0.014	0.007	-0.002	0.036	0.000	0.019			

The table shows pairwise OLS regression of monthly fund flows on performances defined by trailing 12 month returns. The LOWM, MID, HIGHM, HIGH in interaction terms stand for quintile 2, 3, 4, 5 of trailing 12 month returns of sample funds. Regressions are run on cross-section of funds every month. Risk is trailing 12 months standard deviation of fund returns. Flows and risk variables are winsorized at 1% level. Last row is arithmetic average of coefficients from regressions for all months. Robust t-stat is reported in parenthesis.

Table 3-8 Flow-Performance Regression by Month Using One Month Returns

Month	Flow(t-1)	Return (t-1)	Return(t)	LOWM *Return(t)	MID *Return(t)	HIGHM* Return(t)	HIGH *Return(t)	LogTNA (t-1)	Risk(t-1)	Age(t-1)	Constant	Obs.	F	Adj.R2
1	0.425	0.260	0.060	-0.010	0.002	0.051	0.050	-0.004	-0.168	-0.0004	0.033	40965	460.3051	0.2531904
	(47.85)	(39.64)	(5.66)	(-0.62)	(0.11)	(2.91)	(2.73)	(-19.66)	(-11.37)	(-21.16)	(25.72)			
2	0.411	0.045	0.084	-0.065	-0.070	-0.082	0.009	-0.002	-0.077	-0.0003	0.023	38284	424.2361	0.2975304
	(46.31)	(8.70)	(8.86)	(-4.51)	(-4.71)	(-5.06)	(0.53)	(-13.30)	(-6.75)	(-16.86)	(21.37)			
3	0.505	0.046	0.064	-0.028	-0.016	-0.001	0.013	-0.003	-0.111	-0.0003	0.028	40340	431.1871	0.2921677
	(43.46)	(7.87)	(4.24)	(-1.33)	(-0.77)	(-0.06)	(0.67)	(-14.09)	(-9.28)	(-19.14)	(22.53)			
4	0.440	0.019	0.079	0.008	-0.041	-0.062	-0.007	-0.003	-0.011	-0.0003	0.028	39418	380.6	0.2652517
	(41.79)	(2.69)	(5.13)	(0.35)	(-1.77)	(-2.79)	(-0.32)	(-16.70)	(-0.84)	(-17.31)	(22.18)			
5	0.409	0.067	-0.002	0.012	0.042	0.022	0.045	-0.003	-0.011	-0.0003	0.021	39856	334.1372	0.2554706
	(40.90)	(10.13)	(-0.18)	(0.71)	(2.45)	(1.27)	(2.34)	(-14.67)	(-0.74)	(-16.50)	(18.50)			
6	0.417	0.043	0.030	0.009	0.008	0.017	0.038	-0.003	0.018	-0.0003	0.023	40049	322.3545	0.2321233
	(38.94)	(7.48)	(2.52)	(0.49)	(0.46)	(0.91)	(1.87)	(-15.09)	(1.34)	(-15.47)	(20.95)			
7	0.418	0.121	0.045	-0.001	-0.015	-0.004	-0.014	-0.003	-0.017	-0.0003	0.026	41390	372.8498	0.2263072
	(38.24)	(17.81)	(4.37)	(-0.05)	(-0.92)	(-0.24)	(-0.78)	(-16.62)	(-1.28)	(-20.49)	(22.79)			
8	0.413	0.007	0.053	-0.016	-0.024	-0.045	-0.020	-0.003	-0.063	-0.0003	0.026	41168	359.1306	0.2430221
	(40.16)	(1.39)	(4.38)	(-1.03)	(-1.43)	(-2.59)	(-1.01)	(-16.65)	(-4.57)	(-19.14)	(22.94)			
9	0.408	0.013	0.030	0.012	-0.011	0.007	0.009	-0.002	-0.043	-0.0003	0.022	40677	327.0842	0.229435
	(38.43)	(2.41)	(3.82)	(1.05)	(-0.90)	(0.55)	(0.66)	(-12.64)	(-3.52)	(-19.29)	(19.62)			
10	0.456	0.014	0.037	-0.011	0.002	0.026	0.000	-0.003	-0.024	-0.0004	0.028	37450	336.2235	0.2393738
	(35.85)	(2.38)	(2.44)	(-0.55)	(0.10)	(1.37)	(0.01)	(-16.38)	(-2.08)	(-20.64)	(22.58)			
11	0.420	0.040	-0.314	0.326	0.340	0.329	0.357	-0.003	-0.004	-0.0003	0.024	37627	339.216	0.2482713
	(37.26)	(6.15)	(-16.21)	(12.72)	(13.77)	(13.73)	(15.67)	(-14.18)	(-0.36)	(-17.58)	(19.42)			
12	0.448	0.034	-0.745	0.170	0.405	0.559	0.638	-0.003	-0.178	-0.0003	0.046	37223	1238.272	0.3171981
	(47.85)	(39.64)	(5.66)	(-0.62)	(0.11)	(2.91)	(2.73)	(-19.66)	(-11.37)	(-21.16)	(25.72)			
12M Avg.	0.431	0.059	-0.048	0.034	0.052	0.068	0.093	-0.003	-0.057	-0.0003	0.027			

The table shows pairwise OLS regression of monthly fund flows on performances defined by monthly returns. The LOWM, MID, HIGHM, HIGH in interaction terms stand for quintile 2, 3, 4, 5 of monthly returns of sample funds. Regressions are run on cross-section of funds every month. Risk is trailing 12 months standard deviation of fund returns. Flows and risk variables are winsorized at 1% level. Last row is arithmetic average of coefficients from regressions for all months. Robust t-stat is reported in parenthesis.

Table 3-5 shows the result for flow-performance relationship using three factor alphas and Table 3-6. uses four factor alphas. In these two tables, I identify similar patterns to the Table 3-4. No matter which model is chosen, investors are similarly sensitive to these performance measures. Average sensitivity of flows to top three factor alpha decile is 0.677 and average sensitivity of flows to top four factor alpha decile is 0.63, compared to 0.479 found in Table 3-4. The comparative result, if not a digression, is not consistent with Barber, Huang and Odean (2016), who finds that CAPM is the primary asset pricing model fund investors are actually using to evaluate investments. However, it is also worth noting that these are only unconditional relationships. The conditional treatment with all three pricing models can be found in Section 3.5.5. Another similarity is the structural change of these coefficients across the year. The three-factor alpha, four factor-alpha produce a convex flow-performance relationship during January to October, with best funds being chased and worst funds punished, though not as hard. Though it is debatable what factors investors is using to adjust for risks, they react to these performance measure with similar mode. December is also a special month, with strong contrarian interest on low alpha funds and elevated interest on high alpha funds. The coefficient on fund risks largely remain the same with the latter two models. This suggest that the change in risk aversion and change in performance evaluation is two separate aspects.

Figure 3-3 shows average flow-performance relationship from January to November and December only. It is obvious that CAPM, three-factor and four-factor alphas produce similar pattern in January to November period. The sensitivities of flows to these measures is a wedge shape, rather than the established convex relationship. There are some positive sensitivities to the worst performers, albeit less than the sensitivities to best performers. This suggest that worst funds are punished in these periods. Some studies heighten the concern that worst funds are not properly dealt with by investors, like Harless and Peterson (1998); Sirri and Tufano (1998); Berk and Tonks (2007). However, the bottom three lines address part of their concerns: there is a significant shift from momentum to contrarian style in December that drag the average sensitivities of flows to lowest alphas down. The resultant flow-performance function is closer to a traditional convex shape. The only difference of CAPM to the other model is on top performers: investors are somehow chasing the funds with top three-factor and four-factor alpha at year end (their sensitivities are even higher than rest of the year). For CAPM, it is the opposite, which is counterintuitive.

3.5.2 Empirical Flow-Gross Return Function

Like I mentioned in methodology section, the various definitions of performance complexify the topic under investigation. Firstly, it is unclear if investors adjust for risk at all. There is evidence on investors responding to both risk-adjusted and gross performance. For example, Harless and Peterson (1998) finds that investors only account for risk upon choosing the funds. However, studies like Ippolito (1992) and Guercio and Reuter (2014) do find flows chasing risk adjusted performances. Secondly, gross returns and risk adjusted returns are likely to contain different information. Ivkovic and Weisbenner (2009) argue that gross return proxies for tax burden and risk adjusted return reflect skill of managers. These concerns, therefore, motivates us to investigate not only the relationship between flow and risk adjusted return, but also gross returns. The horizons I selected are yearly and monthly returns.

Table 3-7 shows the result for flow-performance relationship using 12-month gross returns, while the flows are one-month flows. The regressions are also done by month. The bottom row computes the average of regression coefficients across months. There is little study that investigates shape of flow-gross return functions. The only case, Franzoni and Schmalz (2017), finds a hump shape. They argue the hump shape results from extreme returns adding noise into fund evaluation process. I do not find the same hump shape. Instead, the last row shows a wedge shape. The average coefficient on the contemporaneous yearly return is 0.021, meaning that the flows are in the same direction of the returns. This implies that the funds with worst yearly returns are punished by investors. By the definition, sensitivities to the second, third, fourth and fifth yearly return quintiles are 0.002, 0.004, 0.007 and 0.028 respectively. The alphas and 12 months return yield similar graphs. There is a strong positive response to the top return funds, and a muted response to the medium quintiles. These are after controlling for the autocorrelation of flows, shown as the 0.394 coefficient on lagged flows. Coefficient on lagged return is 0.011. Flows chase returns, but less than the extent to which they chase alphas. The other rows in Table 3-7 shows these relationships by months. The results show that the relationship change significantly throughout the year. Similar to Table Table **3-4**, Table **3-5**, Table **3-6**, investors are contrarian to all parts of returns only in December, as shown in coefficients for the piecewise regression per month. The contrariness is less than what identified in using alphas.

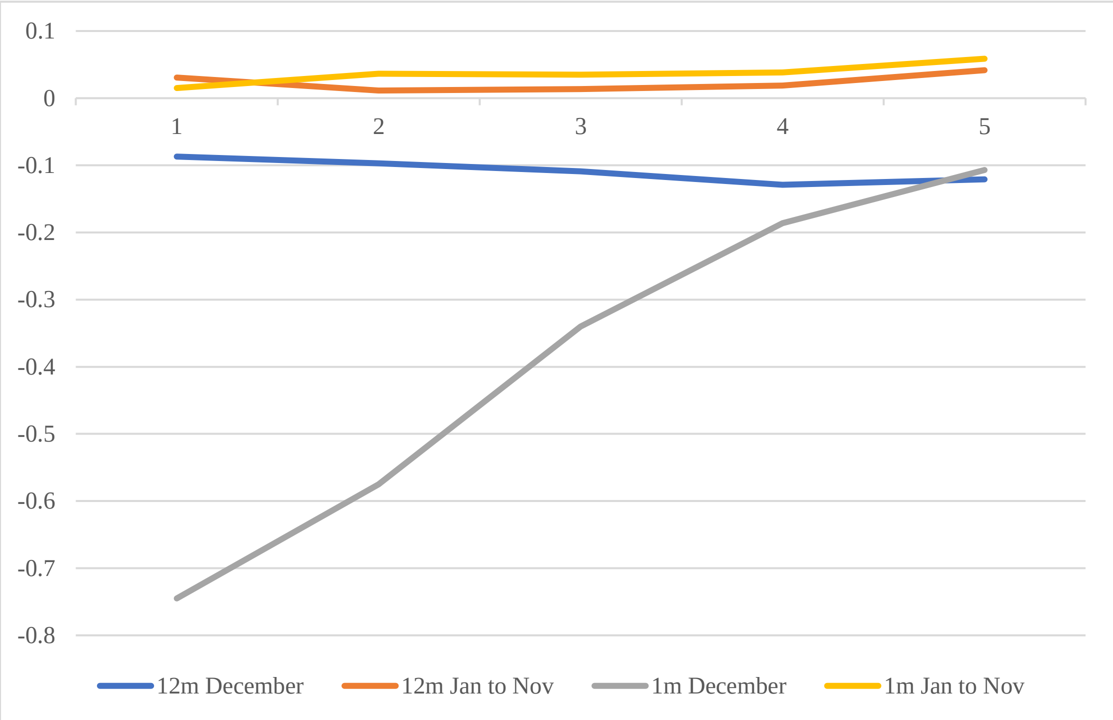


Figure 3-4 Comparison of Shape of Flow-Performance Functions Defined on 12-Month Returns or 1-Month Returns

As a robust check, I also included one-month gross return, in addition to 12-month gross return. Table 3-8 shows results from flow-one month return regressions. I also draw the shape of flow-return functions in Figure 3-4 including one-month and 12 month returns. Lines are drawn for average coefficients in January to November and December alone. The result from January to November is similar to 12-month returns. Average sensitivity to return in the same months is less than 0.1 but higher than 0 in all parts. The positivity implies a momentum trading strategy where investors chase not only yearly, but also monthly return in making fund investments. Nevertheless, the shape of the flow-one month return function is downward sloped compared to 12-month return. Investors are extremely contrarian to bottom quintile returns in December. Compared to results from 12-months return, it is possible that either one-month and 12-month returns convey different information at year end, or investors are slow in incorporating recent returns into their judgement.

3.5.3 Proportion of Gains Realized and Proportions of Lose Realized

In Section 3.5.1 and 3.5.2, I rely on the coefficients from piecewise regressions to model investor behaviour towards fund performance. Although regressions allow us to control for other effects, the coefficients are just conditional correlation between dependent and independent variables. During the process, any structures regarding the signs of flows and returns are smeared. As I mentioned in Section 3.4, it is ideal to distinguish the conditional effect of signed performance on flows. I adopt the methodology of Odean (1998), albeit making some modifications due to lack of micro dataset.

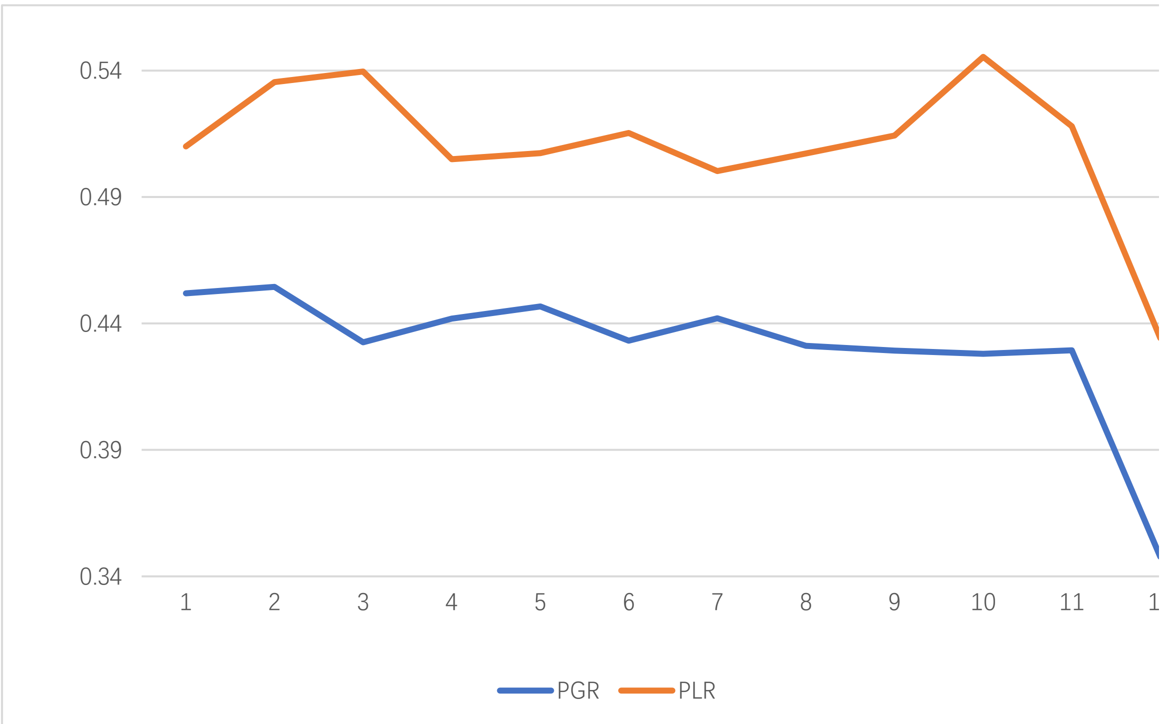


Figure 3-5 Value of PGR and PLR Across Year

Figure 3-5 illustrates a specific version of PGR and PLR throughout the year. At month k, I calculate year-to-date returns for all domestic US mutual funds. The funds are then separated into two groups: a group with positive return and a group with negative returns. They I calculate the proportion of funds with negative year-to-date flows in the positive group and negative group. In general, mutual fund investors are more likely to sell into loses than selling into gains, since the PLRs are higher than 50% and PGRs are lower than 50% in all months. This is consistent with Chang, Solomon and Westerfield (2016) who finds a robust reverse disposition effect among mutual fund investors. Disposition effect predicts higher propensity to sell gainers than losers while reversed disposition effect predicts the contrary. The top line of Figure 3-5 shows PLR for all mutual funds. The tax-loss selling effect predicts that as the year end draws near, investors accelerate realization of their losses. It is the case before October. October marks the highest PLR in a year, with 54.5% of funds with positive year-to-date returns experience outflows. However, PLR in December is not predicted by tax-loss selling effect. The PLR in December is only 0.43, suggesting investors are likely to flow into loser funds of the year in December, rather than leave them. This pattern is similar to the regression results in Table 3-4 and implies a reversal strategy towards losers. It also supports the portfolio rebalance story.

Did the rebalance flows come from exiting flows from gaining funds? We should see the PGR raises near end of year. The PGR lines show that it is not the case. The PGR decrease monotonically throughout the year, meaning that investors hang on to winning funds as the year progress. It has two implications. Firstly, it is consistent with tax-loss selling hypothesis, which predicts that gains will be kept for realization until next year, since tax rate on long term capital gains are lower and there is always chance that these gains can be offset by short term losses. Secondly, it shows that the negative coefficient on lowest return quintile in December from Table 3-7 is due to incremental flows in December picking these funds. There is less evidence on flows rebalancing out of winning funds to losing funds.

3.5.4 Patterns of Flow-Gross Return Modelled by PS

Section 3.5.3 examine the structure of flows conditioned on the sign of returns. Grouping returns into positive and negative territories may not provide enough dispersion to create a visually distinguishable pattern. Since the hypothesis or theories I stated above are centered on returns, I am hoping that separating returns into more groups clarify the issue. In this section, I am presenting a modified version PGR and PLR called PS (proportion of sale). Calculations and definitions are as per in Methodology.

Table 3-9 presents the PS for mutual funds across months. The outside columns show the proportion of funds with outflows (defined on year-to-date flows) among funds in quintiles 1 and 5 of year-to-date returns. PS on these quintiles capture the pattern of flows responding to extreme returns. The table shows a clear tendency of keeping the winners as the year progress. At January, investors are almost neutral towards winner funds in the month, with a PS of 0.495. The PS of this deciles decline significantly and monotonically within the year. As of December, the PS on these top performers are only 0.34, due to either the tax consequence of selling these funds and year end return chasing. The case is different for quintile 1, where the PS increase monotonically until October. This can be perceived as investors considering the tax benefits of realizing these losers immediately. After October, the PS declines as these loser funds attract more inflows, the only plausible explanation being portfolio rebalance. To show the effect visually, Figure 3-6 contains the values of PS through quintile 1 to quintile 5. It is now clear that the year-end anomaly in flow-performance relationship is due to a complex interaction of three effects: tax loss selling, return chasing and portfolio rebalance. The effect from portfolio rebalance is strong to an extent that it overwhelms the other effects. I also know that as there are significant inflows into mutual funds in turn-of-the-year, the flows are favoring losers more than winner funds. It is unclear whether flows rebalance from winner funds into loser funds at the year end, but I do not find it impossible.

Table 3-9 Probability of a Certain Return Quintile is Sold (PS)

Months	PS_Quintile1	PS_Quintile2	PS_Quintile3	PS_Quintile4	PS_Quintile5
1	0.493	0.488	0.487	0.472	0.495
2	0.529	0.501	0.487	0.474	0.463
3	0.522	0.502	0.484	0.451	0.413
4	0.524	0.503	0.477	0.444	0.401
5	0.527	0.507	0.482	0.452	0.402
6	0.546	0.506	0.466	0.442	0.391
7	0.554	0.509	0.467	0.458	0.389
8	0.569	0.516	0.483	0.442	0.385
9	0.561	0.516	0.487	0.448	0.389
10	0.572	0.507	0.492	0.447	0.388
11	0.557	0.507	0.479	0.454	0.386
12	0.492	0.417	0.404	0.380	0.345

The table shows value of Probability of a Certain Return Quintile is Sold (PS) across months. PS in this table is defined by year-to-date return. For example, the last value in Column PS_Quintile1 shows the percentage of funds with outflows measured from January to December while being in quintile 1 of returns from January to December.

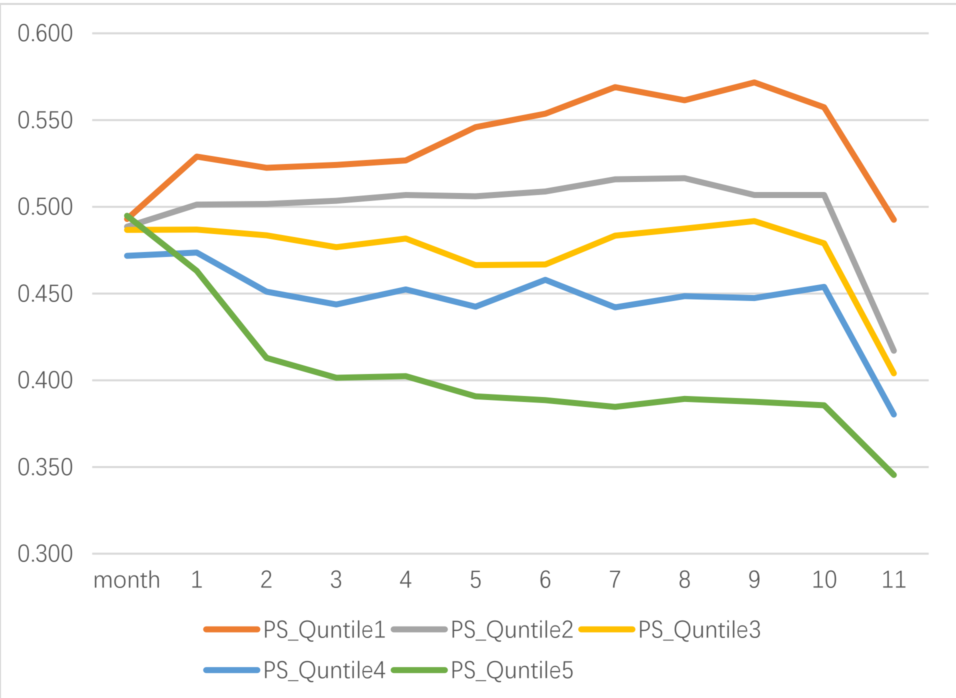


Figure 3-6 Probability of Certain Return Quintile Being Sold (PS)

3.5.5 Formal Regressions

So far, I have examined the flow-performance relationship using different specifications of performance. In Table 3-4, I also control for fund characteristics previous study shown to be vital in determining flows. In reality, the effect from fund characteristics may interact with performance. Some measures of performance may also subsume other measure of performance, since they are weighted stronger in investors evaluation (Barber, Huang and Odean 2016). In this section, I conduct formal regression of flows on fund characteristics. The regressions are carried out on January to November and December alone. Several performance measures, including their lagged values enter regression. I hope that the regression would capture the relative relevance of each performance measures to investors decisions and how these relationships will change at turn-of-the-year.

I also test for other fund characteristic effects on flows and their interactions with calendar months. The first is fee. Many study shows that fee has an adverse effect on flows. Gruber (1996) reports that fees are slightly negatively related to performance. As flows are also positively related to performance, flows act as if they are averse to fees. Sirri and Tufano (1998) also documents that high fees funds attract lower flows and funds that decrease fees attract more flows. Bergstresser, Chalmers and Tufano (2009) relates fees to brokerage in the industry. Funds that charge high fees are usually sold through brokers, who are compensated by a proportion of the sales. They find that these broker directed flows do not earn higher risk adjusted returns. Guercio and Reuter (2014) isolates underperformance of active mutual funds only to funds sold through brokers. Another variable I included is advertisement, proxied by whether a funds reports 12-b1 fee on their SEC filings. Advertisement is commonly showed as an instrument to lower search cost and inflate asset under management. Sirri and Tufano (1998) show that funds with advertisement has higher flow-performance sensitivities than those without. Huang, Wei and Yan (2007) finds advertisements alleviate convexity of flow-performance relationship, since they lower the participation cost. I also include a dummy variable called INITIAL, defined on whether a fund require a minimal initial investment. INITIAL proxy for the audience of the funds, since broker-directed , retail investors are less likely to participate in these funds. I also add a dummy called GROWTH, defined on whether a funds lies in “Growth” category in US Mutual Fund Objective. GROWTH is included to further test the existence of a tax effect.

Growth fund are historically shown to have high turnover, which translates into larger volume of realized capital gains and distributions at the year-end. Since tax-loss selling predicts investors will be reluctant to buy into these funds at the year-end, I see if it is indeed the case.

Table 3-10 reports flow-performance regressions for January until November. Column (1) in Table 3-10 use only gross returns and their lags. Flows are positively sensitive to these performance measures, though coefficient on lagged 12-month returns are not significant. Gross returns alone barely explain flows, with R2 for model 1 being less than 1%. Column (2) use only risk adjusted returns. Their explanatory power is marginally higher than gross returns. CAPM alpha is the dominant determinant. The coefficient on contemporaneous and lagged CAPM alpha is 0.38 and 2.92. When these measures are controlled form, economic significance of three-factor and four-factor alphas are much weaker. Three-factor alphas are only marginally significant. These are consistent with Barber, Huang and Odean (2016) and Berk and van Binsbergen (2016), who finds mutual fund investors only account for market risks. Column (3) contains all performance measures. It is obvious that the economic significance of 12-month returns are suppressed by risk adjusted returns, while the coefficients on one-month returns remains unchanged. Coefficient on CAPM alpha is lower. In Column (4), larger, expensive and risky funds are shown to attract less flows, as documented by literature. Age, again, does not seem to be a determinant of flows. Column (5) contains our dummy variables. Investors do not like advertised funds, though coefficient on ADV is not statistically significant. Funds that require initial investments enjoy higher asset growths and a growth object do not change flows.

Table 3-11 reports flow-performance regressions for December only. The model specifications are similar to the last table. The first impression is that investors in December is very performance-centric. Overall R2 are as much as 21% using returns alone. Column (1) confirms a very strong contrariness. Coefficient on one-month returns are 0.5, meaning that a 1% change in December returns translates into 0.5% of flows in the opposite directions. Flows are also mildly correlated with 12-month returns. Column (2) use only alphas. The

CAPM alpha, once a positive determinant, has similar magnitude with Column (2) in Table #, but the relationship is negative. Flows are also against three-factor alpha. The coefficient on 4f alpha is positive, however it is explained away by the returns in Column (3). The economic significance of CAPM alpha is also partly explained by returns in Column (3), and coefficient on 3f alpha becomes insignificant. The alphas provide only marginal explanatory power on top of Column (1). Two important findings in Column (4) is that investors become risk seeking and high fee funds do not hold flows back anymore. The coefficient on risk becomes positive and fee variable is not significant anymore. Recent studies document seasonal variation in risk appetite of fund investors, like Kamstra *et al.* (2017), who finds higher risk appetite in turn-of-the-year. The result in risk variable fits this pattern. In addition, if the year-end inflows came from individuals who just received their bonuses, it is reasonable to believe that higher fee funds may enjoy a higher proportion of these flows, since individuals are mainly directed by their brokers. The brokers usually charge a markup on fees for their services. Column (5) tells more stories. The coefficient on INITIAL becomes insignificant, which means the institutional funds I have assumed do not attract more flows anymore. This provides support for the impression that individual flows dominate the year-end volumes. Another finding is the negative and significant coefficient on Growth dummy. I interpret this as a reflection of tax concerns, since Growth funds is the funds expected to make distribution and accumulate more unrealized capital gains at year end. Investors foresee the consequence of buying into these funds, thus the less inflows.

Table 3-10 Flow-Performance Regression Using January to November Observations

Column	(1)	(2)	(3)	(4)	(5)
	Model 1	Model 2	Model 3	Model 4	Model 5
1M Return	0.024***		0.030***	0.030***	0.030***
	(0.002)		(0.002)	(0.002)	(0.002)
12M Return	0.010***		0.002	0.002	0.002
	(0.001)		(0.001)	(0.001)	(0.001)
1M Return-1	0.054***		0.052***	0.051***	0.051***
	(0.002)		(0.001)	(0.002)	(0.002)
12M Return-1	0.002		-0.002*	-0.001	-0.001
	(0.001)		(0.001)	(0.001)	(0.001)
CAPM Alpha		0.377***	0.181***	0.122***	0.121***
		(0.034)	(0.030)	(0.034)	(0.034)
CAPM Alpha-1		0.292***	0.475***	0.500***	0.500***
		(0.032)	(0.028)	(0.032)	(0.032)
3F Alpha		0.046*	0.018	0.006	0.006
		(0.023)	(0.023)	(0.024)	(0.024)
4F Alpha		0.077***	0.092***	0.082***	0.082***
		(0.020)	(0.020)	(0.021)	(0.021)
Log(TNA)-1				-0.002***	-0.002***
				(0.000)	(0.000)
Age-1				0.000	0.000
				(0.000)	(0.000)
Risk-1				-0.021***	-0.021***
				(0.003)	(0.003)
Fee-1				-0.002***	-0.002***
				(0.000)	(0.000)
ADV					-0.000
					(0.000)
INITIAL					0.001***
					(0.000)
GROWTH					0.000
					(0.000)
Constant	-0.004***	-0.001***	-0.002***	0.013***	0.013***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Adjusted R2	0.009	0.017	0.021	0.022	0.022
Observations	404681	405282	385476	378300	378300
Sample Funds	3615	3451	3451	3446	3446

The table shows panel regression of monthly flows on performance and characteristics, using observations of January to November. Flows are winsorized at 1% level. Definitions and calculations of performance variables are as per Section 3.1.2. Total Net Asset is from financial reports published by Thomson Reuters. Fees is Total Net Expenses reported in the financial highlights in the annual report. Age is the difference between current year and year first appeared in Datastream. ADV is a dummy variable which takes value one if the 12-b1 fee of funds are non-missing. INITIAL is a dummy variable which takes value one if Thomson Reuters Eikon reports that fund requires an initial investment. GROWTH is a dummy which takes value one if the fund is a growth fund as reported by Thomson Reuters Eikon.

Table 3-11 Flow-Performance Regression Using Only December Observations

Column	(1)	(2)	(3)	(4)	(5)
	Model 1	Model 2	Model 3	Model 4	Model 5
1M Return	-0.507***		-0.562***	-0.526***	-0.528***
	(0.007)		(0.007)	(0.008)	(0.008)
12M Return	0.048***		0.143***	0.104***	0.104***
	(0.004)		(0.007)	(0.007)	(0.007)
1M Return-1	-0.094***		-0.069***	-0.038***	-0.038***
	(0.008)		(0.008)	(0.008)	(0.008)
12M Return-1	0.004		-0.112***	-0.046***	-0.046***
	(0.004)		(0.008)	(0.008)	(0.008)
CAPM Alpha		-3.471***	-1.219***	-0.916***	-0.900***
		(0.086)	(0.121)	(0.128)	(0.128)
CAPM Alpha-1		2.348***	1.995***	1.277***	1.266***
		(0.067)	(0.118)	(0.125)	(0.126)
3F Alpha		-0.362**	0.266*	-0.058	-0.045
		(0.130)	(0.112)	(0.118)	(0.118)
4F Alpha		0.396**	-0.178	0.156	0.138
		(0.122)	(0.102)	(0.109)	(0.109)
Log(TNA)-1				-0.002***	-0.002***
				(0.000)	(0.000)
Age-1				0.000	0.000
				(0.000)	(0.000)
Risk-1				0.144***	0.141***
				(0.014)	(0.014)
Fee-1				-0.001	-0.001
				(0.001)	(0.001)
ADV					0.002**
					(0.001)
INITIAL					0.000
					(0.001)
GROWTH					-0.004***
					(0.001)
Constant	0.015***	0.022***	0.016***	0.017***	0.019***
	(0.000)	(0.000)	(0.000)	(0.002)	(0.002)
Adjusted R2	0.214	0.080	0.232	0.254	0.255
Observations	36707	37649	35406	32857	32857
Sample Funds	3580	3440	3436	3432	3432

The table shows panel regression of monthly flows on performance and characteristics, using observations of only December. Flows are winsorized at 1% level. Definitions and calculations of performance variables are as per Section 3.1.2. Total Net Asset is from financial reports published by Thomson Reuters. Fees is Total Net Expenses reported in the financial highlights in the annual report. Age is the difference between current year and year first appeared in Datastream. ADV is a dummy variable which takes value one if the 12-b1 fee of funds are non-missing. INITIAL is a dummy variable which takes value one if Thomson Reuters Eikon reports that fund requires an initial investment. GROWTH is a dummy which takes value one if the fund is a growth fund as reported by Thomson Reuters Eikon.

3.6 Conclusions

The relationship between flow and performance in the mutual fund industry is under constant scrutiny in academic field. Representing investor's allocation decisions, investment flows to and out of funds reflect their evaluation of the fund quality. Past literature suggests the flow-performance relationship is non-linear and several explanations like strategic change, information cost, strategic fee settings and participation cost. In this study, I examine if there are other exogeneous factors that affect shape of flow-performance relationship, especially calendar related ones.

I anticipate that tax-loss selling and portfolio rebalance may interact with calendar months, which result to shift in flow-performance relationship throughout the year. Funds with large capital gains create tax burden for investors at year end, because short-term capital gains have higher tax rate than long-term capital gains. Investors may be refrained to sell them before next year. In contrast, funds with large capital gains are often funds with large year to date returns. Portfolio rebalancing advices that investors sell them to restore their original weight. Due to their competing implications, I test for these two effects using several methodologies.

I use piecewise linear regression model to measure sensitivity of return to each part of performance (defined by abnormal return and raw return). When performance is defined on rolling CAPM alpha, the average flow-performance function across the year is a traditional convex shape similar to Sirri & Tufano (1998) and Chevalier & Ellison (1997). However, the shape of the function changes materially across calendar months. The most drastic change happens at December when, surprisingly, flows become significantly contrarian to poor performance, turning its sensitivity to poor performance highly negative. Meanwhile, the sensitivity of flows to highest alpha quintile are higher than other times of year. November and December are months with high net inflow of mutual funds. The regression indicates that these inflows favour extreme performers at year end. The inherent structure of panel regression also suggests a reallocation of flows at year end: extreme good performers are gaining money and mediocre performers are losing money.

I also check if the choice of factor models matters for the flow-return function, since asset pricing papers identify factors other than the market and investors may use these more sophisticated models to adjust for risk. I collect data on Fama & French (1993) three factors plus a 12-month momentum factor discovered by Carhart (1997) and compute rolling alphas on three factor or four factor model. The flow-performance function remains qualitatively unchanged across the year compared to result obtained through CAPM alpha. A minor difference is that investors are more sensitive (less contrarian) to highest (lowest) three and four factor alphas quintiles than CAPM alpha.

When performance is defined by gross return, the result is slightly changed. Flows show generally positive sensitivities to extreme 12-month return, indicating flows are punishing worst annual performers and chasing best annual performers, a pattern proposed by Berk & Green (2004). In addition, when performance is measured by monthly return, flows are contrarian to worst performers. However, regression coefficient of monthly return shows that a large part of contrariness to worst performers is shown at November and December, when larger drop in fund NAV coincides with large inflows.

These findings on flow-performance relationship at year end shows a different picture from what depicted by traditional mutual fund studies. The proposition in Berk & Green (2004) is that flow should punish funds with poor abnormal return and reward funds with good abnormal return. Under the assumption of diseconomy of scale, positive alpha funds attract too much capital and their future performance will attenuate. Negative alpha funds maintain a healthy portfolio size and they suffer less from diseconomy of scale. What suggested by our data is that in average, these poor performers are not adequately punished, and most of the effect comes from excessive flows to them at December (and partly November), for some unknown reason. Meanwhile, the best funds enjoy significantly higher growth rate in assets, especially at year end, consistent with the information cost hypothesis of Sirri & Tufano (1998), who emphasize that year-end rankings are salient to consumers.

To deal with flow-performance relationship of gross flows, I developed a measure called PGR (probability of gains realized) and PLR (probability of gains sold). PGR measures the proportions of funds with outflows associated with positive returns in the same month and PLR measures the proportions of funds with outflows associated with negative returns.

The result provides mixed evidence on tax-loss selling. The PGR for mutual funds falls from January until December almost monotonically, suggesting investors are more inclined to hold on capital gains when they are still short-term. However, this pattern is both predicted by tax-loss selling and year end return chasing. Meanwhile, the result on PLR shows that from January, investors increase their realization of capital losses right until October, a time coincides with investment companies facing their TRA tax confirmation deadline. After October, there is a strong tendency that the losing funds are bought back: the PLR plummet to below 50%, which is consistent with our previous regression results.

I also design a measure of the probability of a certain performance quintile is sold called PS (probability of being sold). Gross returns are sorted into quintiles by each month and the percentage of funds with outflows are computed on each quintile. PS capture the shape of flow-return function while considering both inflows and outflows, although it is a pseudo measure of gross flows. Result on PS consolidates our findings from piecewise regressions. For funds with extremely poor return (quintile 1), the PS raise drastically until October, and fall dramatically after October. For funds with extremely good return (quintile 5), PS fall monotonically across the year, while the last two months saw a sharper fall.

I also resort to formal regressions of flows on measures of performance and various fund characteristics previously found to affect flows. The result is as follows: flows are sensitive to all measures of performance in December, as well as ordinary months. However, the explanatory power of CAPM alpha is much higher than three factor and four factor alphas. Flows are also highly contrarian to contemporaneous one-month return and contemporaneous alphas in December. Gross returns also have a very special role in

December, with the four variables alone explaining as much as 21.4% of variation of flows. The explanatory power of alphas is much weaker. For the rest of the year, performance variables barely explain flows.

I also find that at end of year, small, risky, advertised and income (in contrary to growth) fund receive greater flows. Fees, age and initial investment requirement do not have a statistically significant effect. Meanwhile, for the rest of the year, risky and expensive funds experience *outflows*, which is different from turn-of-the-year. Overall, it seems that investors seem to have stronger risk appetite at year end, and their investment becomes highly contrarian.

The conclusion of this chapter is multi-dimensional. In one aspect, the contrarian behaviours of investors at year end supports the portfolio rebalance hypothesis, discussed in Calvet et al. (2009). The data shows that mutual fund investors fight passive variations in their portfolios by buying more losing investments at year end, a time point that coincides with common recommendations for portfolio rebalance. The increased risk appetite at year end is potentially a window-dressing behaviour, as many mutual funds are also held in institutional accounts. These institutions have incentive to increase their portfolio variance to gamble for better year-end ranks (Chevalier and Ellison 1997). In other aspect, it is clear tax has a very strong impact on flow-performance relationship. The patterns identified in the data are consistent with investors harvesting tax-loss and deferring capital gains: investors are reluctant to sell winning investments until January, and ready to realize capital losses well before January. The conjecture is that due to TRA, October 31st marks the end of tax year for many institutions, and many individual investors may recognize this time window. Haug & Hirschey (2006) discuss this possibility: "Since 1986, net capital gains distributions to mutual fund shareholders have been determined without regard to capital losses attributable to transactions occurring during the last two months of the calendar year. Capital losses incurred by mutual funds during the last two months of the year are carried over to the subsequent taxable year. Any seasonal tendencies related to tax-motivated selling by institutional investors after 1986 should thus occur well before the end of the calendar year."

Since mutual funds with poor performance may accumulate large amount of capital losses, and this tax losses are carried forward (and not passed-through to the investors) even if the October 31st has passed, tax savvy investors may regard these funds as economically attractive.

Nevertheless, I still feel hard to differentiate between each explanation, as much as what I have experienced in explaining the January effect in equity research. For example, the contrariness of investors at year end cannot only be explained by tax, but also a (blind) belief in mean-reversion in asset prices. Investors may anticipate the worst performers to bounce back next year. When they are performing their annual strategic review at year-end, they feel justified to include more of these funds. In addition, these beliefs may not be blind at all, since it is discussed in previous literature that bad funds could do better in the future due to personnel change Heuer, Merkle and Weber (2016) or strategic change Lynch and Musto (2003). Another example is that the selloff before October can also be explained by Seasonal Affective Disorder discussed in Kamstra et al. (2017), in which August, September and November marks onsets of SAD and falling risk appetite. At these times, investors may not willing to hold on losing investments even if traditional asset pricing theory suggest higher expected returns.

Whatever the explanations are, it is obvious that these calendar-related factors distort the flows-performance relationship. While previous studies find a convex flow-performance function, this study suggest that much of the convexity are contributed by the last two months of the year, a pattern that cannot be identified using full observations. Future research is directed towards clearer explanations on why fund investors behave differently at different times of the year, whether it is institutional, tax or behavioural.

Chapter 4

Do Flows of Leveraged Funds Reflect Investor Sentiment?

Chapter 4 - Do Flows of Leveraged Funds Reflect Investor Sentiment?

ABSTRACT

Leveraged funds is a relatively new concept in mutual fund world. Most of the leveraged funds seeks a geared exposure on the daily return on certain underlying index. As the construct of these funds are very likely to attract retail day traders, their flows are valuable field for sentiment study. This study obtains a sample of daily flows on nearly all leveraged funds trading in the US. Using principal component analysis, I extract a dominant component interpreted as a bull-bear contrast which is contrarian to market sentiment. Similar to an alternative daily sentiment measure, the component is strongly influenced by sentiment and predict market return revisions on subsequent trading days. The patterns of return revisions are consistent with the prediction of limits of arbitrage hypothesis. In a further test, I do not find evidence that leveraged fund investors benefit from their transactions. The chapter offers advices for both regulators and issuers of these products.

4.1 Introduction

Leveraged (or inversed) Exchange Traded Funds is a burgeoning product originated from beginning of 2010s. Unlike traditional ETFs, these funds are designed to provide a multiple (or an inversed multiple) of the return of the underlying index in a single day. The exposures are achieved by derivatives like return swaps and future contracts. There are several papers which discuss the characteristics and limitations of these products (Avellaneda and Zhang 2010; Little 2010; Lu, Wang and Zhang 2012). Leveraged ETFs are that these are not for the faint hearted. The extra volatilities, higher management fees and unpredictability of return over longer holding periods make it almost exclusively for individual traders (Sullivan 2009; Jarrow 2010; Charupat and Miu 2011). This study investigates whether the investment decisions of leveraged fund investors fit in the stylized behavioural modes of "noise traders", a concept pioneered in De Long *et al.* (1990). In their model, the market participants are either noise trader or rational arbitrageurs. Noise traders has stochastic beliefs on the price of the assets and tend to herd. The collective actions of large amount of noise traders deviate price from fundamental. The deviations can be long-lasting in a way that deter rational arbitrageurs from arbitraging it away. The mere existence of noise traders is a source of systematic which is priced in assets. Later literature refers to the magnitude of these collective actions as investor sentiment. This study acknowledges that the leveraged funds are particularly susceptible to fluctuations in sentiments. I seek proof if there are a sentiment component in leveraged fund flows and whether these are related to market wide sentiments.

From a professional viewpoint, leveraged funds tick no boxes for institutional investments. The problem lies in that these funds are not designed for diversification and hedging, but pure risk exposures. Most of the leveraged funds do not track the long-term performance of an index. Instead, they strive to achieve an exact replication of a multiple of daily performance. This means any daily tracking errors are amplified in the long term by compounding. The characteristic makes any attempt to buy-and-hold or hedge futile. For example, one of the largest funds in this category, the ProShares Ultra S&P 500 ETF (SSO), states this in its prospectus: “This fund seeks to double the return of the S&P 500 for a single day (from one NAV calculation to the next) using stocks and derivatives.” As of end of 2017, the S&P 500 Index has a return of 19.85%, while the SSO yielded 44.98%. The annual tracking error for SSO is a whopping +5.28%, far more than any traditional ETF could bear. To make the matter worse, in a downward market, many negative daily tracking errors are amplified, resulting to higher than expected losses for investors.

It is reasonable to regard these funds as catering for day traders who seek a *bet* on index performance during a certain day so that they enjoy a high-risk and high-return investment profile. This is already a violation of investment objective of institutional investors. Besides, institutional investors do not need these funds to hedge, since they have access to derivatives and margin accounts. A swap or Exchange Traded Notes (ETN) grants institutional investors the ability to replicate index performance at little cost, be it reversed or a multiple. Leveraged funds charge you as much as 3% per year for doing the same thing. Secondly, even if institutional investors seek leveraged exposure on an index, they have way cheaper alternatives like stock index futures and options. These are standardized and guaranteed contracts that reliably deliver pre-defined outcomes. Leveraged funds fills the niche that individuals are restricted (financially or regulatorily) from accessing these products. Avellaneda and Zhang (2010) show that individuals can reduce the buy-and-hold tracking error by rebalancing positions on leveraged funds, however they doubt the ability of individuals to conduct day-to-day dynamic rebalance.

The composition of risk seeking investors and their short horizons makes flows to leveraged funds a great instrument for sentiment study. I believe the availability of leveraged funds data will improve on existent literature. Since sentiment is abstract and not directly observable, previous researches try to approximate the true sentiment via several methods. A class of paper construct sentiment index through extracting information from proxies that best represent the ongoing sentiment condition, for example observable mis-pricing of assets, abnormal activities of equity issuance or liquidity. The most distinguished is Baker and Wurgler (2006a). They select numbers of (and returns on) IPOs, closed-end fund premium, dividend premium, equity issuance and turnover and extract sentiment components through principal component analysis. Huang *et al.* (2013) refined their procedures by running a partial least square before the PCA. The resultant sentiment index offers some improvements. Another group of studies believe that sentiments are best observed from the actual opinions of investors, which can be obtained by survey. Papers like Arif and Lee (2014) or Stambaugh, Yu and Yuan (2012) directly use survey data published by Conference Board or University of Michigan as measures of sentiment. The use of AAII sentiment surveys is also not rare, for example De Bondt (1993). Since the development of processing power, a new type of papers which resorts to textual-based resources like social media, newspaper or online search activities emerge. Tetlock (2007) and Fang, Peress and Zheng (2014) construct sentiment index from semantic analysis of news headlines. Bollen, Mao and Zeng (2011) measure sentiment using mood index derived from real-time twitter posts. Joseph, Babajide Wintoki and Zhang (2011) and Da, Engelberg and Gao (2015) explores search indexes for certain items published by Google.

The selection of leveraged fund flows is a mixture of all above. They are actual portfolio decisions by investors, hence an expression of opinions towards future cash flows as well. Unlike market variables, flows are driven by demand since the supply elasticity of ETFs are near infinity. As Goetzmann, William, Massa and Rouwenhorst (2000) says, there is hardly "better way to understand the factors in the economy that matter most to investors than to look at what portfolios they actually hold and trade". There are precedent of using mutual fund flows as a measure of sentiment, for example Indro (2004); Frazzini and Lamont (2008) or Ben-Rephael, Kandel and Wohl (2012). The successes of these papers are mixed. One instance is the unsettling "smart or dumb money" debate. Some paper finds mutual fund investors has the ability to predict the market (for example Gruber 1996), while some finds exactly the opposite (for example Frazzini and Lamont 2008). The problem lies in that the mutual funds is a trillion-dollar business and their investors are extremely diverse. Passive products like ETFs that serve mainly institutional investors, funds with extreme growth objective that serve risk-seeking individuals, funds with regular income distributions that serve pension funds coexist in the market and they are equally popular. Any effects from sentiment is likely smeared only because of the vast investor base. Our study differs from those by using a sub group of mutual fund investors that are mostly affected by sentiment swings. The characteristics of leveraged funds almost guarantee an isolation from institutional investors. If the sentiment story is true, the investors these funds are appealed to are likely to offer a more dramatic contrast to their peer investors in other assets. In this regard, our study is closely related to Kumar and Lee (2006), who find that retail investors trade in concert and explains comovements in stocks with higher limits to arbitrage. One may be concerned with the validity of the study only using a subgroup of investors. However, the point of the study is not to examine the behaviour of mutuala fund investors as a whole - which has been examined exahausively in the past – but how one may improve on the sentiment study of stock market using concrete, exogenous source of information derived from this sub group. The result will tell us the cross-asset validity of sentiment story. Another advantage of our study is that I measure sentiment in a daily scale, while most other studies use monthly or quarterly data. I believe higher frequency data reveals undiscovered patterns in sentiment studies.

In this study, I obtain a sample of daily fund flows of nearly all actively traded leveraged funds in US. Then I conduct a principal component analysis on their flows and extract the first principal component. The first component explains 15.2% of variations in daily flows and it is treated as a potential proxy for sentiment. In addition, as a horse race and for comparison, I also follow Baker and Wurgler (2006a) to construct an alternative sentiment measure using a set of market indicators, including (but not limited to) VIX, put/call ratio, closed-end fund discount and turnover. Since flows are net of returns, I believe the alternative sentiment measure would to some degree solve the endogeneity issues which many previous sentiment studies suffer.

Our correlation analysis shows that the first component from flows (Comp1 hereafter) is not only strongly correlated with contemporary alternative sentiment measure (Comp1^{alt}), but also all its constituents. For example, correlation of Comp1 and Comp1^{alt} is -0.3. Comp1 is highly positively correlated with aggregate bear fund flows and negatively correlated with aggregate bull fund flows. Higher Comp1 is associated with lower VIX, closed-end fund discount and put-call ratio, indicators traditionally regarded as for market stress. Thus, on paper, Comp1 contains strong influence from sentiment and likely stands for the willingness of leveraged fund investors to trade against sentiment. The result supports the notion that sentiment is market wide, rather than isolated, since Comp1 is derived from fund flows. A similar example is Otoo (1999), who finds that there is strong correlation between consumer sentiment and stock market returns. De Long *et al.* (1991) argues that in order for sentiment to be systematic risk that is priced, the existence of noise traders should be universal, and they must act in concert. This is clearly the case in our study.

I also check the price implication of both sentiment proxies. An important aspect of sentiment theory is that price will be driven temporarily above or below intrinsic value. This means in average price will reverse to fundamentals in the future. I find that Comp1 and Comp1^{alt} predict a similar graph for market returns in the following trading days. When Comp1 is negative, contemporary market return is positive and vice versa. The contemporary effects persist for up to 3 days in the future before the price reverse. For Comp1^{alt}, the pattern is similar. In a later regression analysis, I find that although Comp1 and Comp1^{alt} both provide significant contemporary price effect, Comp1 does a better job predicting price reversal than Comp1^{alt}. In addition, I also check if the price reversal is predicted by the components rather than aggregate flows, since previous study finds significant relationship between return and flows. The result is that aggregate flows do not predict return reversals. Although daily stock returns are often believed to be random walk and barely predictable, our result suggest that daily returns are subjected to swings in market wide sentiment, although reversed shortly. The result in this section is similar to Ben-Rephael, Kandel and Wohl (2011), who find that fund flows cause price pressure in a daily scale which is reversed in 10 trading days, although their primary interest is not sentiment.

The study also contributes to the limits of arbitrage theory by examining the characteristic effects on potential sentiment measures. Shleifer and Vishny (1997) argue that sentiment can persists because there are certain restrains that prevent arbitrageurs to trade against it, the so called "limits of arbitrage". Baker and Wurgler (2006b) developed on their idea and predicts a "Sentiment Seesaw": stocks of certain characteristics are harder to value and thus harder to be arbitraged; These stocks will be more sensitive to sentiment. I test the hypothesis against our data using a similar procedures to Baker and Wurgler (2006a). Firms are grouped by a set of characteristics believed to affect limits of arbitrage: Profitability, dividend payout, age, volatility, etc. When sentiment is defined on the inverse of Comp1 (given the strong negative correlation of Comp1 and Comp1^{alt}), I find some evidence on limits to arbitrage theory. For example, return spread (the average return on next day if sentiment is low minus average return if sentiment is high) is higher for low earning firms than high earning firms by 20% on annual basis. Similar patterns are also found when using Comp1^{alt} and they are more consistent to Baker and Wurgler (2006a)'s results. The above not only provide additional evidence for the limits of arbitrage story, but also extend it to a daily scale.

I hope that the study will help understand the compositions and behaviours of leveraged fund investors. Funds with these characteristics should be dealt with great care when put into a portfolio. As I mentioned above, these funds are unlikely to be a great instrument for cheap, reliable hedging. Our result shows that their investors do not follow the common wisdom either. The governing force among investment flows are heavily influenced by sentiment, and investors may also migrate between fund families to express their directional bets on market conditions.

The structure of this chapter is as follows: Section 2 introduces the methodology and data, Section 3 shows the empirical results and Section 4 discuss and finish the chapter.

4.2 Methodology and Data

4.2.1 Fund Flows and Fund Returns

I obtain a sample of daily fund data from Trimtabs, which is a leading provider of high frequency fund data in U.S. The data range between 01/05/2012 to 08/05/2013, amounting to 255 observations after excluding public holidays. Trimtabs provides us with two spreadsheets, one of mutual funds and another one with ETFs. In the mutual funds spreadsheet, Net Asset Value (NAV), Total Net Assets (TNAs) are reported. In the ETF spreadsheet, NAVs, TNAs and fund shares are reported. Trimtabs enquires these data at end of the day and usually gather them at the next day. This means NAV, TNA and fund shares are reported by managers. In addition, both spreadsheets provide fund specific data, including their ticker, Morningstar category, asset class and fund family. I limit the funds to those with Morningstar category “Trading – Leveraged Equity” and “Trading - Inverse Equity” after consulting The Morningstar US Category Classifications document. Morningstar described the “Trading – Leveraged Equity” as “These funds seek to generate returns equal to a fixed multiple of the short-term returns of an equity index”, the latter as “These funds seek to generate returns equal to an inverse fixed multiple of short-term returns of an equity index”. These descriptions are in consistent to our research objectives. The sample period saw an accelerated entry of leveraged products into the market. To avoid influence from those new funds (which typically experience abnormally large inflows on establishment), I drop funds with its first observation starting during the sample periods. Since the dataset do not report establish date, I check Thomson Reuters Eikon terminal with the establish date using fund ticker. I then drop funds that are less than one years old at start of the sample. In addition, I drop funds with smallest 25% of TNA at the start of the sample, and funds that track sector indexes. The filter leaves us with 37 bear funds and 26 bull funds.

I calculate fund returns and flows as follows. The returns of the funds are simply their percentage NAV change.

Equation 4

$$\mathrm{R_{i,t}} = \frac{\mathrm{NAV}_t}{NAV_{t-1}} - 1$$

While the flows of mutual funds are calculated as such that reflect the percentage growth of TNA net of the percentage growth in portfolio value.

Equation 5

$$\mathrm{Flow}_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1}\left(1 + R_{i,t}\right)}{TNA_{i,t-1}}$$

The description of this specification can be found in Chapter One and Chapter Two of my thesis. The flows and returns are winsorized at 99% level.

Table 4-1 Descriptive Statistics for Daily Leveraged Fund Flows

	Obs.	Mean	Std. Dev.	Skewness	Kurtosis	Count	Avg. TNA
Bear Funds	9,468	0.00153	0.029	1.122	21.904	37	252.323
Bull Funds	6,668	0.00013	0.029	0.431	22.120	26	200.331
Aggregate	16,136	0.00094	0.029	0.825	22.013	63	230.838

The table shows the descriptive statistics for flows of two leveraged fund categories and their aggregates. Sample is from 07/05/2012 to 08/05/2013 excluding public holidays. Bear funds refers to any leveraged funds with objective of inversely tracking an index and bull funds refers to the opposite. The funds contain all actively traded leveraged ETFs and mutual funds in US during the sample period with no less than 240 valid flow observations. Calculations of flows assume occurrence at end of trading day. To avoid influence from extreme values, flows are winsorized at 5% level.

Table 4-1 shows the descriptive statistics for daily flows of bear funds, bull funds and their aggregate. Mean for both fund flows are positive, suggesting continued growth in leveraged funds category. Annualized flow to bear funds are nearly 40% and 3.3% for bull funds. Average fund size for bear funds is 252 million, compared to 200 million for bull funds.

4.2.2 Principal Component Analysis

Our measure of sentiment is extracted from the daily fund flows using principal component analysis. As niche products, individual leveraged funds have noisy flows. Principal components filter out these noises and extract common components. I hope to identify a sentiment component from these flows by matching the characteristics of the extracted components with the empirical evidence on characteristics that correspond to a sentiment measure. Similar methodology can be found in Baker and Wurgler (2006a) and Stambaugh, Yu and Yuan (2014). I follow standard procedures by standardizing each flow series.

Table 4-2 Principal Components Analysis of Daily Leveraged Fund Flows

Panel (A) Top 10 Principal Components				
Number of Obs:238				
Rho = 0.2127				
Trace = 0.053				
Components	Eigenvalue	Difference	Proportion	Cumulative
Comp1	3.286	1.148	0.152	0.152
Comp2	2.138	0.421	0.099	0.251
Comp3	1.717	0.214	0.079	0.330
Comp4	1.503	0.141	0.070	0.400
Comp5	1.363	0.180	0.063	0.463
Comp6	1.183	0.045	0.055	0.518
Comp7	1.138	0.077	0.053	0.570
Comp8	1.061	0.063	0.049	0.620
Comp9	0.999	0.067	0.046	0.666
Comp10	0.931	0.045	0.043	0.709

Table 4-2 Cont.

Panel (B) Fund Loadings on Components

Name	Bull	Comp1	Comp2	Comp3	Unexplained
ProShares UltraShort S&P500	no	0.367	0.091	-0.036	0.457
ProShares UltraPro Short S&P500	no	0.322	0.107	-0.011	0.571
Direxion Daily S&P 500 Bear 3X Shares	no	0.286	-0.010	0.017	0.684
ProShares UltraPro Short QQQ	no	0.253	0.124	0.038	0.709
Direxion Daily Small Cap Bear 3X Shares	no	0.241	0.001	0.057	0.770
ProShares UltraShort Dow30	no	0.234	0.154	-0.002	0.725
ProShares UltraShort QQQ	no	0.232	0.121	0.117	0.722
ProShares UltraPro Short Dow30	no	0.207	0.100	-0.007	0.808
Direxion Daily MSCI Emerging Markets Bear 3X Shares	no	0.180	0.056	-0.052	0.861
ProShares UltraPro Short Russell2000	no	0.118	0.174	-0.017	0.862
ProShares Ultra Nasdaq Biotechnology	yes	0.085	0.004	0.040	0.969
Direxion Daily Mid Cap Bear 3X Shares	no	0.076	0.047	-0.050	0.966
ProShares UltraShort MSCI Japan	no	0.070	0.134	-0.001	0.932
ProShares UltraShort SmallCap600	no	0.040	0.094	0.193	0.885
ProShares UltraShort Russell2000	no	0.032	0.222	-0.131	0.821
ProShares Ultra Dow30	yes	0.032	0.115	0.053	0.953
ProShares Ultra FTSE China 50	yes	0.031	-0.122	0.145	0.907
ProShares UltraPro MidCap400	yes	0.026	-0.121	-0.090	0.939
ProShares UltraShort MSCI Brazil Capped	no	0.021	-0.034	0.033	0.993
ProShares Short MSCI Emerging Markets	no	0.019	0.139	0.086	0.928
ProShares Ultra MidCap400	yes	0.017	-0.127	0.363	0.653
ProShares Ultra MSCI Japan	yes	0.016	-0.070	0.070	0.974
Direxion Daily MSCI Developed Markets Bear 3X Shares	no	0.011	0.101	0.198	0.882
ProShares UltraShort MidCap400	no	0.010	0.088	-0.076	0.965
ProShares UltraPro Short MidCap400	no	0.006	0.107	0.293	0.772
ProShares UltraShort FTSE China 50	no	0.004	0.119	-0.197	0.872
ProShares UltraPro Dow30	yes	-0.001	-0.046	-0.105	0.969
Direxion Daily Russia Bear 3X Shares	no	-0.004	0.074	-0.179	0.912
Direxion Daily Mid Cap Bull 3X Shares	yes	-0.007	0.026	0.148	0.948
Direxion Daily Latin America Bull 3X Shares	yes	-0.008	-0.069	0.139	0.942
ProShares Ultra FTSE Europe	yes	-0.015	-0.089	-0.001	0.977
ProShares Ultra SmallCap600	yes	-0.018	0.007	0.046	0.994
AdvisorShares Ranger Equity Bear ETF	no	-0.018	0.115	-0.204	0.867
ProShares Ultra Russell2000	yes	-0.026	-0.016	0.024	0.995
ProShares Ultra MSCI Emerging Markets	yes	-0.027	-0.047	-0.203	0.897
ProShares Short Real Estate	no	-0.028	-0.033	0.064	0.985
ProShares UltraShort Russell2000 Growth	no	-0.029	0.070	-0.151	0.931
Direxion Daily MSCI Developed Markets Bull 3X Shares	yes	-0.029	0.081	0.338	0.718
ProShares UltraShort MSCI EAFE	no	-0.032	0.141	0.061	0.933
Direxion Daily FTSE China Bear 3X Shares	no	-0.033	-0.006	0.032	0.994
ProShares Ultra S&P500	yes	-0.033	0.154	-0.357	0.639
ProShares Short S&P500	no	-0.034	0.331	0.051	0.688
ProShares Short Dow30	no	-0.035	0.122	0.058	0.947
ProShares Short FTSE China 50	no	-0.059	-0.109	-0.022	0.953
ProShares Short MidCap400	no	-0.060	0.064	-0.106	0.950
Direxion Daily S&P 500 Bull 3X Shares	yes	-0.069	0.051	0.212	0.872
Grizzly Short Fund	no	-0.074	0.065	0.010	0.967
ProShares UltraPro Russell2000	yes	-0.078	0.026	-0.074	0.962
ProShares Short SmallCap600	no	-0.079	0.123	-0.144	0.887
ProShares Short Russell2000	no	-0.080	0.295	0.052	0.729
ProShares Ultra MSCI Brazil Capped	yes	-0.085	-0.077	0.041	0.952
ProShares UltraPro QQQ	yes	-0.107	-0.009	0.028	0.954
Direxion Daily MSCI India Bull 3X Shares	yes	-0.108	-0.101	-0.001	0.928
Direxion Daily FTSE China Bull 3X Shares	yes	-0.109	-0.198	-0.005	0.846
ProShares Short MSCI EAFE	no	-0.115	0.249	0.070	0.768
ProShares Ultra QQQ	yes	-0.125	0.105	0.142	0.864
ProShares Short QQQ	no	-0.136	0.260	0.036	0.739
ProShares UltraShort MSCI Emerging Markets	no	-0.137	-0.042	-0.065	0.913
Direxion Daily Russia Bull 3X Shares	yes	-0.161	-0.018	0.014	0.899
ProShares UltraShort FTSE Europe	no	-0.180	0.197	0.040	0.765
Direxion Daily Small Cap Bull 3X Shares	yes	-0.189	0.253	-0.006	0.686
Direxion Daily MSCI Emerging Markets Bull 3X Shares	yes	-0.202	0.129	0.040	0.794
ProShares UltraPro S&P500	yes	-0.217	0.129	0.043	0.768

This table shows principal component analysis for leveraged fund flows in sample, using all valid observations. As we require a minimal observation of 240 per fund, the blank observations are filled using average of the adjacent valid observations. Calculations of flows assume occurrence at end of trading day. To avoid influence from extreme values, flows are winsorized at 5% level. Bear funds refers to any leveraged funds with objective of inversely tracking an index and bull funds refers to the opposite.

Table 4-2 shows the result for principal components. Panel (A) is a list of components ranked by proportions of variance explained. For conciseness I only list the top 10 components. Apparently, the first component, explaining 15 percent of variance, is a major common component. The second component explains nearly 10 percent of variance. The top 10 components explain 70% of total variance. The components exceeding 10th explain a minor part of variance and they are noisy. Thus I do not report them. As of now I do not know specifically what these components stands for, since PCA is only a data reducing instrument. To identify these components, further tests are needed. A preliminary investigation is given in Panel (B) of Table 4-2, which shows the fund loadings on these components. The funds are ranked by their loading on the first component. Since I pool the bear and bull funds, the bearishness or bullishness of the funds is most likely a predominating systematic component of flows. It is the case, at least by eyeballing Panel (B). The top 10 funds by loadings on component one is all bear funds. In addition, their name suggest that these are mostly domestic funds tracking major stock indexes. There are only one style fund and only one foreign fund. For example, the first fund, with a 0.367 on the first component, is a fund replicating -2x of daily S&P500 return. The last funds fund is a 3x bull fund tracking daily S&P 500 return. Their unexplained part of variance is relatively low. Thus, the first component is likely to be reflecting flows from domestic bull to bear funds.

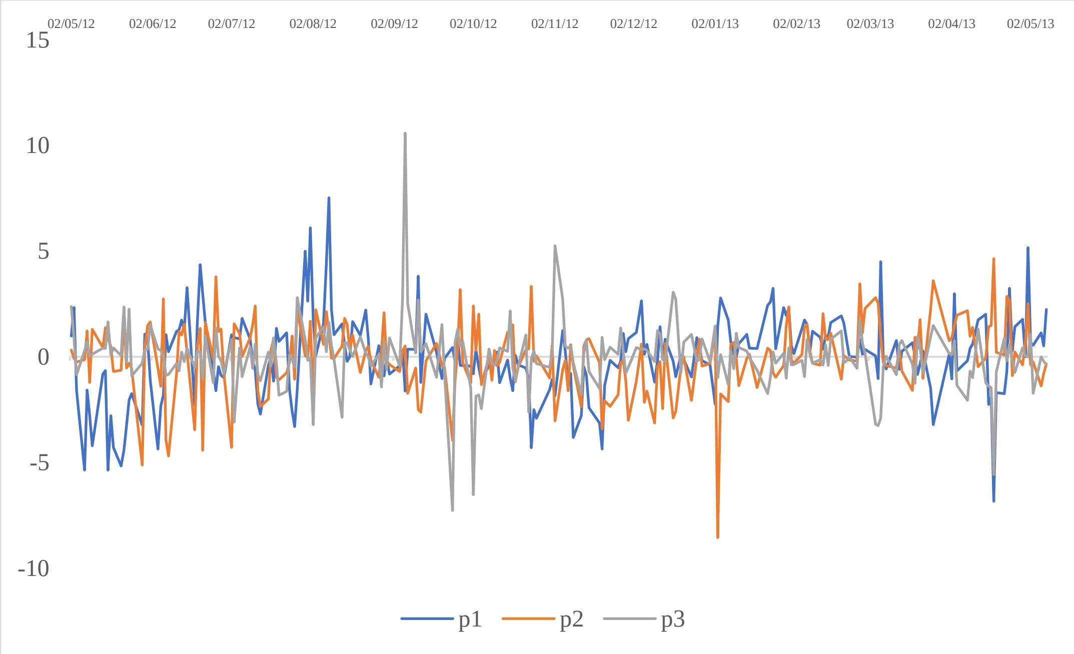


Figure 4-1 Time Series of First Three Principal Components from Daily Leveraged Fund Flows

I also plot the time series of the first three components in Figure 4-1. The components are volatile as much as flows are. By the nature of PCA, the three components should be perfectly uncorrelated. Besides, the level and moments of the series are stable across sample period. They all pass standard unit root tests. In later sections, I mainly examine the characteristic of the first component (Comp1 thereafter).

4.2.3 An Alternative Daily Sentiment Measure

To identify and compare the sentiment measure from fund flows, I also propose an alternative sentiment measure extracted from daily stock market condition variables. The selection of these variables is according to past literature on noise trading and sentiment. Then I take the first principal component from these variables as the alternative sentiment measure ($Comp1^{alt}$ thereafter). In fact, these variables, identified in the past as "proper" sentiment measures, suffer from endogeneity issues, since they are more or less derived from secondary market price. In comparison, fund flows are net of return and reflect actual portfolio decision of investors. From this perspective our sentiment measure from flows is the "proper" measure. Nevertheless, the multi-dimensionality of investor sentiment motivates us to relate the two.

The first variable I include is Chicago Board Options Exchange (CBOE) market volatility index, or commonly known as VIX index. VIX data is collected from CBOE website. The index is computed from daily implied volatility from options on the S&P 100 index. The options used in the calculation of the VIX are the closest in-the-money and out-of-the-money calls and puts of the two front month contracts. When investors foresee worse market condition, they bid up price of put options and sell call options, driving the index higher. The VIX is widely regarded as a fear gauge of market participants. The "Black Monday" of 1987, the 2008 world financial crisis and 2012 European debt crisis all saw a spike in VIX index. Simon and Wiggins (2001) shows VIX is a contrarian predictor of daily S&P 500 returns and profit can be made by trading against VIX. Baker and Wurgler (2006b) suggest the VIX as an alternative sentiment measure. Ben-Rephael, Kandel and Wohl (2012) relates a sentiment measure from monthly mutual fund flows to change in VIX and finds a negative contemporary correlation.

Another variable is the CBOE Total Exchange Volume Put/Call Ratio. The data is collected from CBOE website. This is also an option derived sentiment measure. The Put/Call ratio is calculated by dividing trading volumes on put options by trading volumes on call options. As put options are used to hedge against market weakness or bet on a decline and call options are used to hedge against market strength or bet on an advance, the variable is a bearish indicator of future market condition. The Put/Call Ratio above one indicate bearishness and bullishness when below one. Since Put-Call Ratio is computed from trading volumes and purchases of put and call options represents opposite bets, it is driven by demand rather than supply. This characteristic is similar to fund flows.

I also include the turnover on Nasdaq Index as a sentiment measure. Turnovers are computed daily by dividing trading volume (CRSP Item VOL) over number of shares outstanding (CRSP Item SHROUT). I then compute equal weighted average of turnovers of the Nasdaq Index. Value weighted average is not used as I want to account for the size effect in turnover. There are some disputes regarding whether turnover is a valid sentiment measure. However, many established theories support its inclusion. De Long *et al.* (1990) argues that the dominant participation of noise traders and inability of arbitrageurs to arbitrage them out is the key to sentiment. Baker and Stein (2004) shows that under lagged information dispersion and short-sale constraints, high turnover is a symptom of too much irrational investors. Scheinkman and Xiong (2003) establish a model where overconfidence and disagreements generate a bubble component in asset prices. Some agents believe that they can pass the asset to one who are more optimistic than them in the future. By this mechanism, a small difference of opinions can spark a transaction, accompanied by rising turnover and liquidity. Empirically, several papers link the hike in trading volumes to historical bubbles, like Lamont and Thaler (2003). Turnover are also used to construct a sentiment measure, the most well-known being Baker and Wurgler (2006a).

To account for the role of illiquidity characterizing anecdotal market distresses, I include the Amihud (2002) measure of illiquidity as a sentiment measure. The Amihud illiquidity for stock i is computed as the daily absolute return divided by its dollar volume at that day.

Equation 6

$$ILLIQ_{i,t} = \frac{|R_{i,t}|}{VOLD_{i,t}}$$

Where the daily returns are computed using the CRSP daily return formula which accounts for distribution, reinvestment and compounding:

Equation 7

$$R_{i,t} = \frac{\frac{prccd_{i,t}}{ajexdi_{i,t}} * trfd_{i,t}}{\frac{prccd_{i,t-1}}{ajexdi_{i,t-1}} * trfd_{i,t-1}}$$

PRCCD is the daily close price, AJEXDI is the daily adjustment factor and TRFD is the daily total return factor. The dollar volume is simply the close price multiplies by trading volume.

The individual illiquidity indexes are then averaged across market:

Equation 8

$$ILLIQ_t = \overline{ILLIQ_{i,t}}$$

The Amihud measure ILLIQ is the sensitivity of return to volume, thus it reflects the market impact of one unit of trade. It is parsimonious and can be computed daily without relying on astronomical amount of micro structure data. Baker and Stein (2004) shows that the price impact of trade of this sort is likely a sentiment measure. Liu (2015) finds that Amihud measure of illiquidity fall when sentiment is high, and sentiment Granger cause market liquidity. Although several paper like Cherkes, Sagi and Stanton (2009) distinguish the liquidity and sentiment effect of asset price reversals, Da, Engelberg and Gao (2015) argues that liquidity shock and sentiment may be two sides of a same coin (p15). This motivates us to include liquidity related variable.

Following Simon and Wiggins (2001), I obtain the Trading Index (TRIN) from NYSE website. The TRIN, or often called ARMS index, is regarded as a short-term sentiment indicator by many technical analysts. It is also continuously displayed on NYSE's central wall display among other major indexes. TRIN compares number of advancing issues and declining issues while adjusting for their relative volume:

Equation 9

TRIN = (# of advancing issues / # of declining issues) / (volume of advancing issues/volume of declining issues)

The index is a bearish, or contrarian indicator. When market condition worsens, there are a lot of large transactions on the declining issues and small transactions on the advancing issue, making the index higher than one. However, it also a signal that future price will reverse, since the sellers have exhausted their trades. In a calm market the index reading is around one. In bullish market the index is lower than one. By using TRIN, I hope to catch the volume related conditions that closely resembles the mood of technical traders.

I also include two indicators for safe-haven effect. One is the junk spread and another is the ratio between spot gold and oil prices. Junk spread is the difference between Barclays US Corporate CCC Yield and Barclays US Corporate AAA Yield. The two series are taken from the Bloomberg Terminal. Gold is the widely regarded safe heaven asset (Baur and Lucy 2010; Baur and McDermott 2010) and oil price is related to aggregate economic activities (Hooker 1996; Sadorsky 1999; Baumeister and Kilian 2016). In downward market, many investors switch from consumptions and investments to safer assets. Gold/oil ratio captures the relative demand of safe heaven assets while adjusting for common distractions like inflation.

Ever since the discussion in Lee, Shleifer and Thaler (1991), closed-end fund discount is regarded as a sentiment indicator. Lee, Shleifer and Thaler (1991) calls it a puzzle since their trading price on the secondary market are often lower than the share value reported by managers. They gather possible explanations and reach a conclusion that sentiment is a major cause. They find that closed-end fund discount is correlated across funds and related to return on small stocks. A possible explanation is based on noise trader theory of De Long *et al.* (1990). Undiversifiable fluctuation in the mood of small investors can lead to fluctuations in demand of closed-end funds, hence the discount. From Datastream Terminal, I gather daily Net Asset Value (NAV), market cap and close price P from an official US closed-end fund constituent list. The list contains all active and inactive closed-end fund since 2005. I calculate aggregate closed-end fund discount using the following formula:

Equation 10

$$DIS_t = \overline{NAV_{\iota,t} - P_{\iota,t}}$$

DIS is constructed as a bearish indicator because it is the inverse of the numerical value of the actual difference between market value and NAV. A positive DIS stands for discount and negative DIS stands for premium. To capture potential size effect, The DIS is either equal weighted or value weighted (by end-of-the-day market cap). The sample contains 414 closed-end funds, with market cap ranging from 2.7 billion Dollar to only 19 million Dollar. To avoid influence from extremely small funds, I limit the minimal market cap to 100 million Dollar. The final sample contains 347 funds, with total assets of 158 billion.

Table 4-3 Descriptive Statistics for US Closed-End Fund Discounts

	Obs.	Mean	Std.Dev	Min	Max
EWDiscount	255	0.30%	0.93%	-1.65%	2.43%
VWDiscount	255	0.63%	0.89%	-1.04%	2.78%

NAV represents the Net Asset Value as published by the fund manager. Price refers to the official closing price. Closed end funds are defined by Datastream terminal and are selected by rank of market capitalization. Asset type of selected closed end funds include but not limited to equity, bond, debt & loan and precious metal. The market cap used for weight are calculated by shares outstanding as in quarterly financial reports and official close price.

Table 4-3 shows the descriptive statistics for closed-end fund discounts and Figure 4-2 plots them graphically. Daily equal weighted discount is 0.3% while value weighted discount is 0.63%. The difference suggest big funds tends to discount more. Funds start with an aggregate discount of around 1% at start of the sample but they do not show a clear trend. During middle part of the sample funds switch to a premium, followed by a sharp increase of discount before the end of the year. The graph illustrates the potential fluctuation in the market wide mood of closed-end fund investors.

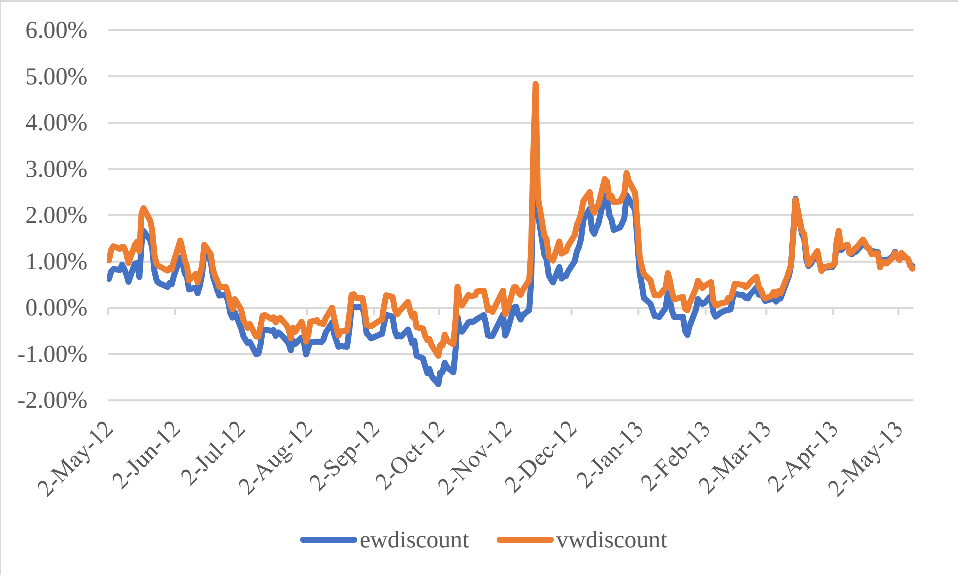


Figure 4-2 Time Series Plot of US Closed-End Fund Discounts

Recent studies on sentiment emphasize the importance of non-market measures of sentiment. These measures directly incorporate investor opinion thus are free from endogeneity. For example, American Associate of Individual Investors (AAII) publish several survey-based sentiment readings every week. University of Michigan also has a monthly survey on consumer sentiments. Unfortunately, the nature of our study entails even higher frequency. As a solution, I follow Da, Engelberg and Gao (2015) to include three non-market variables, the ADS Index, EPU Index and Google Trends Index. ADS Index is a daily measure of concurrent economic activities developed by Aruoba, Diebold and Scotti (2009). ADS is achieved by extracting latent variables from economic activity variables of different frequencies using dynamic factor models. The variables used include weekly initial jobless claims; monthly payroll employment, industrial production, personal income, manufacturing and trade sales; and quarterly real GDP. ADS Index is obtained from Federal Reserve Bank of Philadelphia. Another variable is the Economic Policy Uncertainty (EPU) Index developed by Baker, Bloom, and Davis (2013). The EPU is a news-based index of perceived economic policy uncertainty. It is calculated from counting number of US newspaper articles archived by NewsBank Access World News database that fall into a certain category related to economic perspectives. I also adopt two variables from Google Trends database. One is the Index for item “bull market” (Bull_Trend) and another is the Index for item “bear market”

(Bear_Trend). Google Trends index is a direct measure of the intensity of search activities. The index can be restricted by time, frequency, region and topic. To improve relevance, I restrict the index criterion to US market and "Business" topic. Google Trends data has been used on sentiment analysis. For example, in Da, Engelberg and Gao (2015), the authors compile a "FEAR" sentiment index from a series of Google Trends daily indexes. Since FEAR Index is not provided by the authors, I use our own instead.

Table 4-4 Descriptive Statistics for Daily Market Variables Used for Alternative Sentiment

	Count	Mean	Median	Std Dev.	Min	Max	t-stat
EWDiscount	255	0.003	0.002	0.009	-0.017	0.042	5.178
VWDiscount	255	0.006	0.005	0.009	-0.010	0.048	11.317
Illiquidity	255	6.200	5.610	2.590	1.860	24.710	38.272
Bull_trend	255	0.237	0.083	1.044	-1.938	4.122	3.629
Bear_trend	255	0.173	0.062	1.003	-2.147	3.619	2.747
VIX	255	16.259	15.710	3.039	11.300	26.660	85.421
Junk Spread	255	1.502	1.434	0.216	0.875	1.889	110.962
Put/Call	255	0.943	0.920	0.133	0.630	1.450	112.878
Turnover	255	10.541	10.514	1.804	3.613	16.813	93.312
TRIN	255	1.145	1.040	0.513	0.220	3.430	35.647
Gold/Oil	252	17.999	17.740	1.304	15.180	20.280	219.059
EPU	255	151.557	142.060	61.758	27.220	366.820	39.188
ADS	255	-0.219	-0.254	0.304	-0.872	0.565	-11.492
Mean Flow	255	0.001	0.001	0.004	-0.015	0.015	3.479
Bear Flow	255	0.002	0.002	0.006	-0.021	0.021	3.834
Bull Flow	255	0.000	0.000	0.007	-0.025	0.026	0.315

To avoid influence of extreme values, all series are winsorized at 1% level. For Convenience, the illiquidity variable is multiplied by 10^5. Bull_trend and Bear_trend variables are downloaded from Google Trends website. As the tool allows restriction by regions and subjects, I restrict our region to US and subject to Business and Finance. Since the website do not allow extraction of more than 3 months, I download data for the sample by 4 batches. I then standardize each part using sample means and standard deviation before stitching the data. As Google Trends data is relative, levels of the series do not have meaningful interpretations. Turnover of NASDAQ is provided by Datastream. Gold/Oil ratio uses spot Gold USD price trading in COMEX and spot crude oil USD price in ICE. Mean fund flows are weighted by market capitalizations. Individual fund flows are trimmed at 1% level. Bear flows and bull flows are defined the same as previous tables.

Table 4-4 provides the descriptive statistics for these sentiment related variables. In addition, I include the equal weighted mean flows for all leveraged funds, bear funds and bull funds. The table are informative of the average market condition during the sample. For example, the mean of VIX is 16.259, however it can be as high as 26.66 and as low as 11.3, showing significant shift in market pickiness. The same is for junk spread: average spread between BBB and AAA corporate bonds is 1.5%, or 150bp per year. Highest spread during sample is 1.889% and lowest spread in sample is 1.5%. There is a starker contrast for illiquidity. In extreme illiquidity condition where a small trading can result to large price impact, the maximum illiquidity index can be 24.71, meaning that one-dollar trading volume can result to 2.5bp of absolute daily return for a single stock, while in most liquid day the number is 0.1bp. The positive mean for TRIN and EPU suggest a bearish market in general, while a negative mean for ADS suggest a worse than average economic condition. The aggregate flow to leveraged funds is 0.001% per day, or 0.24% per year, a sign of mild growth in leveraged products. The growth is driven more by bear funds than bull funds, supposedly an aftermath of market turmoil in 2011.

Table 4-5 Principal Components Analysis of Daily Sentiment Related Variables

Panel (A) Top 5 Principal Components

Number of Obs: 906,789
Rho = 0.5375
Trace = 13

Components	Eigenvalue	Difference	Proportion	Cumulative
Comp1	2.69506	0.241762	0.2073	0.2073
Comp2	2.4533	0.613557	0.1887	0.396
Comp3	1.83974	0.551061	0.1415	0.5375
Comp4	1.28868	0.199565	0.0991	0.6367
Comp5	1.08912	0.134547	0.0838	0.7205

Table 4-5 Cont.

Panel (B) Variable Loadings on Components

Name	Comp1	Comp2	Comp3	Unexplained
VWDiscount	0.5449	-0.2125	-0.0161	0.08857
EWDiscount	0.5122	-0.2731	0.0246	0.1089
ADS	0.4531	0.034	-0.2441	0.3343
Put/Call Ratio	0.2824	0.1857	0.4012	0.4044
VIX	0.2448	0.4597	0.2496	0.2054
EPU	0.1767	0.1987	-0.3473	0.5971
Turnover	0.1647	0.1084	0.186	0.8344
Gold/Oil Ratio	0.155	0.3991	-0.3174	0.3591
TRIN	0.0576	0.1857	0.253	0.7888
Bear_Trend	0.0325	-0.1777	0.4245	0.5882
Bull_Trend	-0.0019	-0.229	0.4081	0.5649
Illiquidity	-0.0077	-0.2465	-0.1402	0.8146
Junk Spread	-0.0948	0.4935	0.1728	0.3233

I run a principal component analysis on the variables, hoping to capture their common movements which best represent daily market-wide sentiment. All the variables are standardized beforehand.

In Table 4-5, I show the top 5 principal components and the factor loadings from the sentiment related variables. The first component explains more than 20% of total variance and the eigenvalue is 2.69. The second and third component has also double-digit explanatory power. The five components combined explain 72% of total variance, a lot higher than what we found in Table 4-2. This is expected since the variables used in Table 4-4 are selected on purpose and they carry more concrete information. Mutual fund flows are noisier comparatively. They share less in common so that there are less dominant common components. I hope the loading chart in Panel (B) help us identify the components. Variables are already ranked by loadings on the first components. The highest loadings are seen on closed-end fund discounts, a traditional paradigm of sentiment. Meanwhile, most of their variances are predicted by other variables. The ADS, reflecting concurrent economic conditions, and VIX comes closely behind. Reasonably, the first components drives the common fluctuations in sentiment. VIX, Gold/Oil ratio and junk spread has high loadings on component 2 while Illiquidity has large negative loading. Anecdotally, these variables often accompany turmoil periods in financial markets, in which appetite for safer asset is higher and liquidity is lower. It is obvious that Component 2 is a flight-to-haven variable capturing the crisis states in the market. Component 3 is likely an internet-based sentiment measure given high loadings of Google Trends Variables, reflecting high-frequency, active opinion of the small investors.

4.3 Empirical Results

4.3.1 Correlation Analysis

To identify the Comp1 extracted in 4.4.2.2, I examine their correlation with our alternative sentiment measure $Comp1^{alt}$ and the original variables used in 4.4.2.3. For convenience, all the variables except for Bull_Trend, and ADS in 4.2.3 are constructed to be bearish. A higher read in these variables are associated with worsening market condition, meanwhile a bearish mood of investors. A valid sentiment measure from leveraged fund flows should at least be correlated significantly with these variables. The sign of the correlations will tell the direction of the effects. In Table 4-6, I present pairwise correlation between these variables. I also add equal weighted mean flows of bull/bear funds and their aggregate for convenience.

In the first place, I check if our alternative sentiment measure is reasonable. Consistent with Panel (B) of Table 4-5, $Comp1^{alt}$ serves well as a bearish sentiment measure. It correlates significantly and positively with some of the bearish variables like VIX, junk spread, TRIN and EPU. VIX plays a very important part, showing a correlation of more than 0.8. It is not a surprise since VIX has been regarded as a fear gauge of the market. It is a component of the widely cited CNN Fear Index. $Comp1^{alt}$ is also correlated with both equal weighted and value weighted closed-end fund discount. The negative correlation with illiquidity shows that when sentiment is high, the market is more liquid, which is a potential result of the dominance of many uninformed traders in the market. These uninformed traders are more likely to trade because of overconfidence and heuristic bias. When many uninformed traders make trade in the same direction, more uninformed traders are attracted into the market and everyone is willing to accept a higher price, which is commonly above the fundamental. The second component (alternative) is negatively related to most of these variables, compared to the first component.

The first pattern from Table 4-6 is that the Comp1 is negatively correlated with $Comp1^{alt}$. The correlation is strong and significant at 0.3. This is intriguing since the two measures are from different market: the sentiment measure from the portfolio decisions of a small sample of fund investors are related to sentiment measures from the broad equity and derivative market. This help to strengthen the impression that sentiment is a market wide phenomenon. As described in De Long *et al.* (1991) and Shleifer and Vishny (1997), noise traders can survive in the the market as long as they dominates and deter rational arbitrage attempts. Without effective arbitrage, the collective movements of these investors are a source of systematic risk itself and should be priced in every asset. Similar to us, many studies confirmed sentiment in asset class, time and country scale. For example, Baker, Wurgler and Yuan (2012) has found both regional and global sentiment factors and Cornelli, Goldreich and Ljungqvist (2006) found an association between pre- and post- IPO sentiments.

Table 4-6 Correlation Between Principal Components from Leveraged Fund Flows and Alternative Sentiment Measures

	Component 1	Component 2	Component 1_alt	Component 2_alt	mean flow	mean bear flow	mean bull flow	ewdiscount	vwdiscount	illiquidity	bull_trend	bear_trend	vix	junk spread	put/call ratio	nasdaq turnover	TRIN	gold/oil ratio	EPU	ADS
Component 1		0	-0.301	-0.052	0.047	0.393	-0.449	-0.159	-0.195	0.107	-0.005	-0.057	-0.323	-0.110	-0.242	-0.138	0.026	-0.115	-0.070	-0.267
Component 2	0		-0.146	-0.190	0.618	0.720	0.038	-0.055	-0.106	-0.068	-0.036	0.049	-0.042	-0.065	0.115	0.011	-0.048	-0.242	-0.233	-0.192
Component 1_alt	-0.301	-0.146		0	-0.082	-0.260	0.218	0.112	0.222	-0.325	-0.295	-0.198	0.816	0.544	0.499	0.299	0.294	0.668	0.427	0.471
Component 2_alt	-0.052	-0.190	0		-0.079	-0.182	0.119	0.514	0.562	0.275	-0.231	-0.262	-0.339	-0.596	-0.269	-0.028	-0.291	0.284	0.440	0.668
mean flow	0.047	0.618	-0.082	-0.079		0.776	0.532	0.017	-0.019	-0.011	-0.042	0.072	-0.024	-0.039	0.053	0.062	-0.088	-0.137	-0.143	-0.085
mean bear flow	0.393	0.720	-0.260	-0.182	0.776		-0.122	-0.076	-0.153	0.000	0.000	0.053	-0.152	-0.088	-0.023	-0.049	-0.073	-0.302	-0.207	-0.262
mean bull flow	-0.449	0.038	0.218	0.119	0.532	-0.122		0.129	0.176	-0.017	-0.064	0.043	0.167	0.056	0.113	0.163	-0.041	0.188	0.052	0.218
ewdiscount	-0.159	-0.055	0.112	0.514	0.017	-0.076	0.129		0.978	0.107	0.094	0.116	0.102	-0.331	0.247	0.052	-0.066	-0.141	0.032	0.481
vwdiscount	-0.195	-0.106	0.222	0.562	-0.019	-0.153	0.176	0.978		0.078	0.067	0.080	0.162	-0.286	0.249	0.110	-0.059	-0.011	0.109	0.556
illiquidity	0.107	-0.068	-0.325	0.275	-0.011	0.000	-0.017	0.107	0.078		-0.035	-0.053	-0.175	-0.304	-0.032	-0.251	0.029	-0.184	0.032	-0.057
bull_trend	-0.005	-0.036	-0.295	-0.231	-0.042	0.000	-0.064	0.094	0.067	-0.035		0.451	-0.050	-0.085	0.038	0.147	-0.042	-0.239	-0.186	-0.090
bear_trend	-0.057	0.049	-0.198	-0.262	0.072	0.053	0.043	0.116	0.080	-0.053	0.451		0.022	-0.055	0.113	0.015	0.004	-0.209	-0.131	-0.063
vix	-0.323	-0.042	0.816	-0.339	-0.024	-0.152	0.167	0.102	0.162	-0.175	-0.050	0.022		0.681	0.532	0.144	0.231	0.323	0.133	0.171
junk spread	-0.110	-0.065	0.544	-0.596	-0.039	-0.088	0.056	-0.331	-0.286	-0.304	-0.085	-0.055	0.681		0.153	-0.040	0.050	0.267	0.013	-0.154
put/call ratio	-0.242	0.115	0.499	-0.269	0.053	-0.023	0.113	0.247	0.249	-0.032	0.038	0.113	0.532	0.153		0.209	0.342	-0.017	0.001	0.094
nasdaq turnover	-0.138	0.011	0.299	-0.028	0.062	-0.049	0.163	0.052	0.110	-0.251	0.147	0.015	0.144	-0.040	0.209		0.130	0.121	0.058	0.122
TRIN	0.026	-0.048	0.294	-0.291	-0.088	-0.073	-0.041	-0.066	-0.059	0.029	-0.042	0.004	0.231	0.050	0.342	0.130		0.052	-0.001	-0.042
gold/oil ratio	-0.115	-0.242	0.668	0.284	-0.137	-0.302	0.188	-0.141	-0.011	-0.184	-0.239	-0.209	0.323	0.267	-0.017	0.121	0.052		0.441	0.432
EPU	-0.070	-0.233	0.427	0.440	-0.143	-0.207	0.052	0.032	0.109	0.032	-0.186	-0.131	0.133	0.013	0.001	0.058	-0.001	0.441		0.252
ADS	-0.267	-0.192	0.471	0.668	-0.085	-0.262	0.218	0.481	0.556	-0.057	-0.090	-0.063	0.171	-0.154	0.094	0.122	-0.042	0.432	0.252	

The table shows pairwise correlation coefficient of variables defined in Section 2.3. Sample is from 07/05/2012 to 08/05/2013. All flow variables are winsorized at 1% level. Mean flows are weighted by Components are as defined by Section 2.3. All variables are from official sources otherwise stated.

The first column of Table 4-6 is informative of the structure and characteristic of the Comp1, which I expect to reflect sentiment. It seems to be the case, since it is significantly related Comp1^{alt} albeit negatively. It is also negatively correlated to most of the market condition variables. The correlation between Comp1 and VIX is -0.323 and with value weighted closed-end discount is nearly -0.2. Meanwhile, the bear flow is significantly positively correlated with Comp1 and bull flow is significantly negatively correlated with component one. These patterns tell us two facts: firstly, the dominant component that drive leveraged fund flows reflects the migration from bull to bear funds; secondly, this dominant component move to the opposite direction of the (bearish) market sentiment, meaning that a significant amount of leveraged fund investors is contrarian to market sentiment. When sentiment is high (bullish), investors move from bull funds to bear funds. The explanation could be that these investors actively bet against daily sentiment. When daily sentiment is high, they foresee the potential reversion in asset prices in the next few days, which drive them to unwind position in bull funds before end of the day, resulting in net outflows. These investors may shift their portfolio into bear funds, along with new investors that wish to bet on the price revision. Interestingly, the aggregate leveraged fund flow has little correlation to both component one and the alternative sentiment measure. It is counterintuitive that the component that explain most variation in all leveraged funds is the migration between bull and bear funds, rather than their mean. However, in hindsight, this is a confirmation of the function of these class of funds: an instrument for directional bets, rather than a simple investment product.

4.3.2 Unconditional Return Predictability

In 4.4.3.1, I found that Comp1 from leveraged fund flows as closely related to the contemporary market sentiment, Comp1^{alt}. In addition, I found significant association to established sentiment measures. However, for Comp1 to qualify for a valid sentiment measure, further examination should be conducted. A traditional way is to look at return revision. As De Long *et al.* (1990) points out, the accommodation of noise traders will drive the price from fundamental value. To be specific, they bring demand shock (the “hold more” effect) to speculative assets; buy high sell low (the "Friedman" effect); hold off rational arbitrageurs (the "create space" effect). In a short term, under bullish sentiment, they enjoy higher expected return by investing in "glamour stocks", and vice versa. In the long run, the price of the asset will revise to its fundamental value since the temporary sentiment wears off. Previous sentiment studies rely highly on the identification of price reversals, for example Lee, Jiang and Indro (2002); Baker and Wurgler (2006b); Tetlock (2007). I follow their steps to examine the future stock returns conditional on past sentiment measures. If the Comp1 is related to sentiment, I expect price revisions in future trading days in the opposite directions.

Preliminarily, I examine average future index returns. The return I select is the CRSP US Total Market Index from CRSP Database. The index consists of nearly 4,000 constituents across mega, large, small and micro capitalizations, representing nearly 100% of the U.S. investable equity market. I compare the conditional effect of Comp1 and Comp1^{alt} on future market returns. The procedure is non-parametric: I calculate the average index return up to seven trading days in the future based on the sign of Comp1 and Comp1^{alt} at day 0.

Table 4-7 Future CRSP Total Market Returns Given Day 0 Value of Comp1 and Comp1^{alt}

Panel (A) Return on CRSP Total Market Index Conditional on Signs of Comp1									
		t+0	t+1	t+2	t+3	t+4	t+5	t+6	t+7
t=0	Negative	0.099%	0.165%	0.215%	0.012%	0.008%	0.027%	0.007%	0.027%
	Positive	0.040%	-0.017%	-0.024%	0.137%	0.206%	0.157%	0.187%	0.144%
	t(negative-positive)	2.767	4.084	9.903	-2.757	-3.703	3.118	3.032	2.186
Panel (A) Return on CRSP Total Market Index Conditional on Signs of Comp1^{alt}									
		t+0	t+1	t+2	t+3	t+4	t+5	t+6	t+7
t=0	Negative	0.209%	0.093%	0.060%	0.033%	0.113%	0.161%	0.137%	0.141%
	Positive	- 0.048%	0.037%	0.078%	0.120%	0.073%	0.027%	0.055%	0.040%
	t(negative-positive)	5.119	3.145	-1.039	-1.98	2.453	1.882	1.604	0.313

The table shows CRSP Total Market Index return k days later (k>=0) given a positive or negative value of day 0 component values. CRSP Total Market Index contains nearly 4,000 constituents across mega, large, small and micro capitalizations, representing nearly 100% of the U.S. investable equity market. The components do not need to be re-centered since all components will have zero mean in PAC analysis. Figures in table represents average daily returns.

Table 4-7 shows the result on the grouping procedure and Figure 4-3 visualize these mean returns. Note that since Comp1^{alt} represents bearish sentiment, negative values of

$Comp1^{alt}$ indicate bullishness and positive values of $Comp1^{alt}$ indicate bearishness. Likewise, negative values of Comp1 accounts for bearishness and positive values of Comp1 accounts for bullishness. Figure 4-3(a) shows that when Comp1 is negative, the contemporary return is larger than would be if Comp1 is positive. The difference is nearly 6 basis point daily, or 15% annually. The differences are even higher at t+1 and t+2. However, at t+3, there is a material return revision. The average returns on negative Comp1 at t+0 are higher than average returns on positive Comp1 at t+0 by 12.5bp daily, or 31.25% annually. The return revision is both statistically and economically significant. The return revisions continue well into t+7, with the differential returns being significantly negative. Figure 4-3(b) shows average returns on market index seven days in the future, based on the sign of $Comp1^{alt}$. As can be noticed from Table 4-6, Comp1 and $Comp1^{alt}$ is significantly negatively related, I would have expected an inversed graph from Figure 4-3(b). However, it is not the case. Negative values of $Comp1^{alt}$ is associated with higher contemporary returns. The contemporary return difference is 25.7 basis point daily, or 64.25% annually. Unlike Figure 4-3(a), the price revision happened immediately after t+0. At t+2, the return difference is already negative, yet not statistically significant. At t+3, the return difference is negative and significant. Although there is a positive and significant rebound in return difference, there is no significant return difference after t+5.

The patterns in Figure 4-3(a) and Figure 4-3(b) shows the actual return revisions subjected to fluctuations in sentiment, albeit defined differently. As I noticed in Table 4-6, leveraged fund investors are contrarian to market sentiment since they hold bear funds in bullish mood and bull funds in bearish mood. Figure 4-3(a) shows their gain and losses for up to a week. When sentiment defined on Comp1 is bullish (Comp1>0), the contemporary return is high as well, since sentiment is the very force that boost price to the current level, presumedly above fundamental. Leveraged fund investors seem to foresee the price revision that ensue and take position in bear funds. Under bearish sentiment, they would have chosen bull funds. However, although the price does reverse after t+3, they need to wait two days it to happen. Given the expanding return difference at t+1 and t+2, it is questionable whether they will stick to their position, as any exposure in these funds are amplified by the inherent leverage. Those cannot withstand the fluctuation during the two-day holding period will suffer great losses. In fact, Charupat and Miu (2011) find that these investors do have very short holding periods.

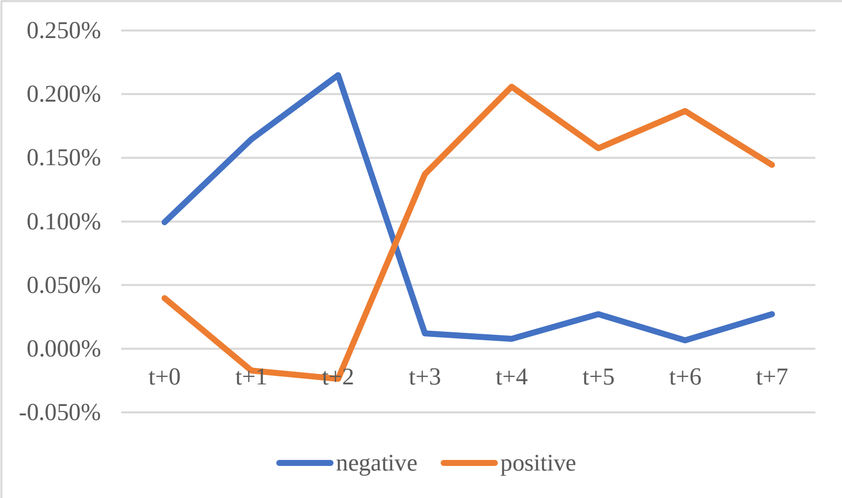


Figure 4-3 (a) Future Market Returns Conditioned on Comp1

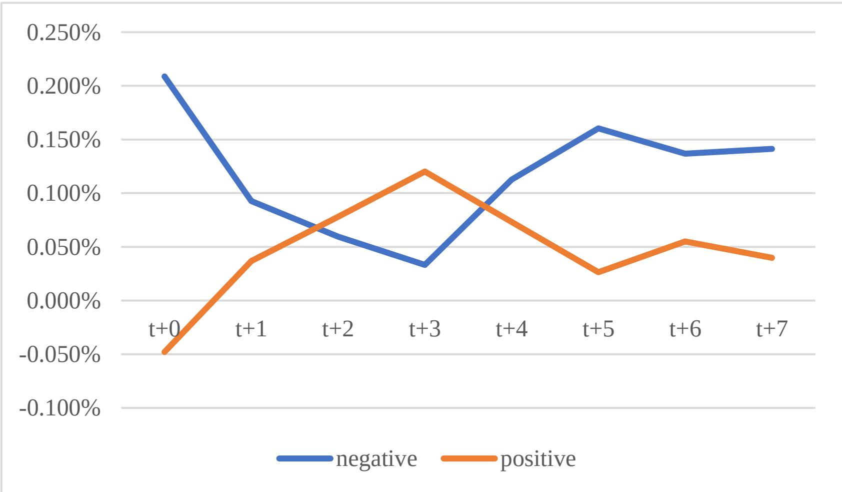


Figure 4-3 (b) Future Market Returns Conditioned on Comp1^{alt}

Figure 4-3(b) shows the return revision as would be predicated by a traditional sentiment measure. When the market is bullish (Comp1^{alt}<0), the return is higher than in bearish period. High sentiment should correspond to price bubble in the short term and pessimism should lead to temporarily low price. The price will not be corrected immediately by rational arbitrageurs because of limits to arbitrage, as argued by Shleifer and Vishny (1997). Figure 4-3(b) suggest that the correction happened rather quickly and permanently in a daily scale, as the return differences are not significant after t+4.

4.3.3 Limits to Arbitrage and Conditional Equity Returns

A key element for sentiment to be systematic is limits to arbitrage. As activities of noise traders create mispricing, rational arbitrageurs have incentives to do exactly the opposite to these noise traders, hoping for price to converge to fundamental. Limits to arbitrage are factors that deter these arbitrage behaviours. Limits to arbitrage is one of the core assumptions in DSSW model, where arbitrageurs are described as short horizon, financially constrained and disciplined and noise traders herd in short or even longer terms. The prospect that price will not converge in short run deters these arbitrageurs since they do not want to bear unnecessary risks. As highlighted by Baker and Wurgler (2006a), the extent to which stock mispricing can be arbitraged depends on the ambiguity of the stock's valuation, often revealed by stock's characteristics. In this section, I make one more step to test for these effects. I make subgroups of stocks based on their characteristics and explore the sentiment effects from Comp1 and Comp1^{alt}.

Table 4-8 T+1 Returns on Stocks Sorted by Characteristics Conditioned on Signs of Comp1

Comp1alt		Sdt. Dev	Market Cap	Tangibility	Research	BE/ME	Sale Growth	Ext. Finance	Dividend Payout	Earnings	Age
	decile1	31.25	18.20	42.50	34.50	44.00	21.35	34.75	31.50	19.98	29.00
	decile2	38.00	46.50	33.00	-51.00	36.75	25.25	41.75	51.25	41.75	26.25
	decile3	38.50	49.00	32.50	52.25	46.25	30.50	34.75	55.00	42.50	40.50
	decile4	41.50	46.25	38.25	47.00	50.50	40.00	34.75	38.25	42.00	35.25
	decile5	41.75	45.50	40.25	51.50	44.25	41.25	38.75	39.00	38.75	37.50
negative	decile6	49.25	52.25	42.00	43.75	40.50	41.50	40.00	39.50	46.00	38.50
	decile7	41.25	46.75	42.00	47.25	41.75	46.25	34.75	35.75	46.00	34.00
	decile8	40.75	48.00	35.00	41.25	38.00	40.50	38.25	45.25	45.75	36.25
	decile9	33.25	46.75	45.75	38.50	32.00	42.75	40.00	41.25	48.25	43.50
	decile10	21.65	44.75	37.50	18.93	15.73	53.25	36.00	44.25	40.00	43.50
	Mean	37.72	44.40	38.88	32.39	38.97	38.26	37.38	42.10	41.10	36.43
	decile1	10.70	4.33	9.48	6.75	0.08	-5.20	-2.12	-0.33	-9.98	7.73
	decile2	4.83	6.70	-2.05	31.25	11.75	10.78	-1.05	2.12	3.38	7.78
	decile3	0.67	-3.80	2.31	-3.50	1.83	-1.53	7.83	-3.53	3.15	-0.75
	decile4	4.03	8.08	-0.90	-1.57	4.43	6.65	5.70	4.20	8.53	9.18
	decile5	5.45	8.90	0.19	-5.03	3.60	2.21	3.70	9.83	10.70	1.08
positive	decile6	-0.66	1.60	0.87	3.73	4.75	5.25	5.43	2.26	8.15	6.35
	decile7	2.13	2.90	2.63	6.88	1.82	8.88	10.65	0.59	1.67	3.78
	decile8	-0.79	2.95	6.83	2.19	3.10	6.68	3.50	-0.18	5.33	5.43
	decile9	6.93	1.76	-9.93	-9.10	-6.28	0.49	2.29	11.70	1.06	2.39
	decile10	4.00	1.89	-8.85	-14.70	-7.60	10.43	1.75	-2.05	-2.85	-0.07
	Mean	3.73	3.53	0.06	1.69	1.75	4.46	3.77	2.46	2.91	4.29
	N	626442	627847	509443	272803	487951	615666	618444	487951	480107	628373

The table shows the annualized market cap weighted average stock returns at t+1 given t+0 signs of Comp1 and stock characteristics. Sample dates are from 07/05/2012 to 08/05/2013. Sample stocks contains all active primary issues in NASDAQ, AMEX and NYSE measured at 01/31/2012. I only consider stocks with age of more than 5 years. Characteristics are calculated using CRSP North America Annual Update Database and defined as such: Total Risk = rolling standard deviation of quarterly returns; Earnings = ROE = (IB+TXDI-DVP)/(CEQ+TXDIC); Market Value= P*CSHO ; Dividend Payout = DVPSX*CSHO/(TXDITC+CEQ); Tangibility = PPEGT/AT; R&D Expenses = XRD/AT ; BE/ME = CEQ/P*CSHO; External Finance = (ΔAT-ΔRE)/AT; Sale Growth = ΔSALE/AT and AGE = current year – date stock first available in CRSP. Non-positive values of Earnings and dividend yield are considered as decile 0.

Table 4-9 T+1 Returns on Stocks Sorted by Characteristics Conditioned on Signs of Comp1^{alt}

Comp1^{alt}		Sdt. Dev	Market Cap	Tangibility	Research	BE/ME	Sale Growth	Ext. Finance	Dividend Payout	Earnings	Age
	decile1	18.23	20.25	34.25	31.50	33.25	20.45	26.00	28.25	21.15	32.00
	decile2	21.00	24.48	25.00	25.25	33.00	25.25	31.00	31.75	30.75	27.00
	decile3	19.78	25.75	24.30	24.18	29.25	22.38	29.00	29.50	27.50	25.75
	decile4	23.98	34.25	21.78	26.50	32.00	28.25	24.55	28.75	27.00	28.75
	decile5	24.33	34.00	24.95	27.00	27.25	22.70	24.13	25.75	27.50	27.00
negative	decile6	25.75	35.00	27.75	33.50	30.25	24.30	23.20	22.65	30.50	27.75
	decile7	29.50	34.00	31.50	28.50	25.25	32.25	29.25	21.18	28.00	25.50
	decile8	29.00	32.25	27.00	25.25	23.43	29.50	23.23	25.75	30.25	27.75
	decile9	33.75	31.50	23.75	16.38	18.03	28.00	27.75	30.00	30.75	25.25
	decile10	37.75	27.00	20.63	12.15	21.08	40.50	29.50	22.98	24.95	25.50
	Mean	26.31	29.85	26.09	25.02	27.28	27.36	26.76	26.66	27.84	27.23
	decile1	19.65	1.06	12.00	7.53	7.15	-8.23	5.40	-1.66	-13.58	10.08
	decile2	18.43	19.03	0.77	14.00	12.73	7.53	6.68	13.55	9.33	2.42
	decile3	16.43	11.10	7.48	16.88	12.00	2.02	8.63	12.40	12.50	9.65
	decile4	15.20	14.13	9.20	15.45	15.60	14.25	11.35	8.13	17.60	10.83
	decile5	14.78	12.55	8.83	14.50	13.93	13.18	10.88	14.55	14.23	7.28
positive	decile6	14.78	11.43	7.90	6.58	9.83	16.55	15.73	11.83	17.43	9.33
	decile7	10.30	10.48	7.38	16.63	12.38	17.45	10.35	10.15	14.40	7.88
	decile8	6.85	12.20	10.65	13.58	11.60	12.45	12.40	15.35	14.30	11.85
	decile9	-0.54	13.45	10.50	6.65	2.01	10.18	8.15	17.25	14.88	14.93
	decile10	-15.18	14.58	1.73	-12.20	-15.10	16.83	4.00	16.85	6.93	12.50
	Mean	10.07	12.00	7.64	-9.24	8.21	10.22	9.36	11.84	10.80	9.67
	N	626442	627847	509443	272803	487951	615666	618444	487951	480107	628373

The table shows the annualized market cap weighted average stock returns at t+1 given t+0 signs of Comp1 and stock characteristics. Sample dates are from 07/05/2012 to 08/05/2013. Sample stocks contains all active primary issues in NASDAQ, AMEX and NYSE measured at 01/31/2012. I only consider stocks with age of more than 5 years. Characteristics are calculated using CRSP North America Annual Update Database and defined as such: Total Risk = rolling standard deviation of quarterly returns; Earnings = ROE = (IB+TXDI-DVP)/(CEQ+TXDIC); Market Value= P*CSHO ; Dividend Payout = DVPSX*CSHO/(TXDITC+CEQ); Tangibility = PPEGT/AT; R&D Expenses = XRD/AT ; BE/ME = CEQ/P*CSHO; External Finance = (ΔAT-ΔRE)/AT; Sale Growth = ΔSALE/AT and AGE = current year – date stock first available in CRSP. Non-positive values of Earnings and dividend yield are considered as decile 0.

The data on stock returns, financial variables and identification information are collected from the annual update file of Compustat-CRSP North America database. The stocks consist of all 9,818 active, primary issues of NASDAQ, AMEX and NYSE that existed during the sample period. Return data are daily and accounting data are quarterly. As stock information tends to lead accounting variables by one to two quarters, I match the daily data with accounting data lagged one quarter, similar to Fama and French (1992). For example, the corresponding accounting data for return and flow on 20, August 2012 is dated Q2 2012. The daily available data is not lagged. I do not lag by the same length as Fama and

French (1992) as their data frequency is not as high. Following Baker and Wurgler (2006a), our variables includes (CRSP item codes in parenthesis): Total Risk (rolling standard deviation of quarterly returns); Earnings ((IB+TXDI-DVP)/(CEQ+TXDIC)); Market Value; Dividend Payout (DVPSX*CSHO/(TXDITC+CEQ)); Tangibility (PPEGT/AT); R&D Expenses (XRD/AT); BE/ME (CEQ/P*CSHO); External Finance ((ΔAT-ΔRE)/AT); Sale Growth (ΔSALE/AT) and age in years. The companies are sorted into deciles based on these variables. I notice that there are many companies that do not have profit and do not pay dividend at all. Instead of dropping them, I the negative and zero values into decile 0, as these companies have special bearings on sentiment effects. For concerns that the small companies in NASDAQ and AMEX may result in clustering of large but significant companies in the top deciles, I use the NYSE breakpoints for deciles.

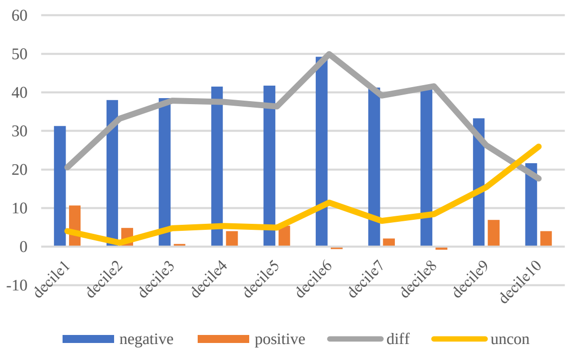
Baker and Wurgler (2006a) argues that these variables proxy for limits to arbitrage. For example, small, young, unprofitable, non-dividend-paying and volatile companies may build higher barrier to arbitrageurs since these companies are limited in liquidity, have higher asymmetry in information and accommodates more individual investors. Growth, valuation and external finance may also play a role since these variables reveal the prospect of the company and signal distresses, although the authors suggest a saddle-shaped relationship. I am curious about the joint effect of Comp1, Comp1^{alt} and these variables on the price corrections in the future. If Comp1, Comp1^{alt} reflect market sentiment, the companies that has higher limits to arbitrage should exhibit higher price reversion following a high absolute level of sentiment. For example, companies with small market capitalization should have higher return after low sentiment than big companies and vice versa, because small companies are more difficult to value which deters arbitrageurs from trading against sentiment mis-pricing.

Table 4-8 shows the annualized t+1 return on equal weighted portfolios of all NASDAQ, NYSE and AMEX stocks conditioned on the signs of Comp1 at t0. The return observations are bi-sorted by characteristics and day 0 signs of Comp1, a potential proxy for market sentiment condition. The last row on positive or negative groups is the unconditional mean returns. Note that simply sorting by negative and positive signs of Comp1 w I e create a tremendous difference in returns. The annualized returns on days when the last reading of Comp1 was negative is 35-40%, while the returns are only single digit after positive Comp1, consistent with our previous result. This return reversion is hardly explained by traditional consumption-based theory. However, the key figures to look at in this table are the differences in returns on each decile when they are conditioned on signs of Comp1, as these shows the magnitude of return reversions for stocks with different characteristics under different market conditions. For example, the average return on decile 1 of stocks measured by quarterly standard deviation (the most non-volatile stocks) after a negative Comp1 is 31.25%. The figure could have been 10.7% for the same portfolio under a positive Comp1 is only 10.7%. The 20.55% difference alone is not very meaningful. However, if I do the calculations on each of the standard deviation deciles, I know the conditional effect of volatility on the return reversal. The same applies for every characteristic sorting scheme. For convenience, the differences are calculated and visualized in Figure 4-4. In addition, in Figure 4-4 I also calculate the mean returns of portfolio deciles, which do not appear in Table 4-8. The results are similar to Baker and Wurgler (2006a) and Da, Engelberg and Gao (2015). For example, the effect of earning, size, age and dividend payout on spread increase with their decile ranks, albeit less monotonical for dividend payout. Considering the former result in which Comp1 has a strong negative correlation with (bearish) market sentiment, the effect is exactly the opposite to what would have been resulted by a (bearish) sentiment. These supports the assumption that small, non-profitable, young and non-dividend-paying firms are associated with higher limits to arbitrage, and sentiment-induced mispricing are exacerbated by these limits. There are some discrepancies to Baker and Wurgler (2006a). For example, the return spread for total risk portfolios is not monotonic. Instead, it is hump shaped. The theory predict that risky portfolios should be most susceptible to sentiment. The hump-shaped function found in Baker and Wurgler (2006a) for BE/ME, EF/A, Sale Growth do not appear in our results, which are hard to interpret given the ambiguous implications of these variables. In conclusion, the dominant component in leveraged fund flows is associated with similar price corrections to what a traditional sentiment measure would have been expected. As a validation, the yellow lines seem to reflect many stylized findings on the risk-return tradeoff in financial market. The downward yellow lines in Graph (c) and (g) shows the famous size and value effect, which are thoroughly discussed in Fama and French (1992). In addition, the role of total risk seems to be quite significant in daily scale, as shown in Graph (a), although it is not the primary focus of this chapter.

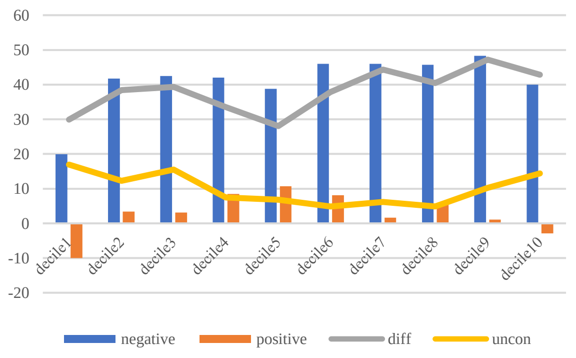
As a horse race and for cross-check, I also repeat the procedure on Comp1^{alt}. The price implications for Comp1^{alt} is shown in Table 4-9 and Figure 4-5. We can see that the result fits Baker and Wurgler (2006a) much better than Comp1. There are monotonic relationships between return spread in T+1 and total risk, earnings, dividend payout, tangibility and age, and the directions of the effects are expected. The t+1 annualized return spread on non-profitable companies (decile1) is 34.7%, while for the most profitable companies it is only 18.25%. For the youngest companies (decile1), the t+1 return spread is 22% per year while for the most established companies it is only 13%. The most striking effect is found on total risk, where most volatile companies produce 53% annualized return spread, compared to a negative figure for the least volatile companies. In addition, the hump shaped relationships predicted by Baker and Wurgler (2006a) are also found on Graph (g), (h) and (i).

Figure 4-5 and Figure 4-5 provide evidence that Comp1 and Comp1^{alt} are measures of market wide sentiment, because the same mechanism in which certain characteristics of the asset exacerbate the sentiment-induced price correction are also observed on the relation between these two variables and asset prices. Values of Comp1 and Comp1^{alt} not only predict price reversion, but also the reveal conditional effect of characteristic on magnitude of price reversion. I am aware that the limits to arbitrage channel is weaker when based on Comp1 than Comp1^{alt}. This can be reconciled by their construction: the Comp1^{alt} is constructed the similar way to Baker and Wurgler (2006a), in which established measure of market stress and mispricing are selected; Comp1 is extracted from mutual fund flows which contain not only investor opinions on future trajectories of fund performance, but other prospective on idiosyncratic fund attributes. In other words, Comp1 comes from individual assets and Comp1^{alt} comes from aggregated variables. The key to the finding is that components extracted from different markets and by different variables both predict asset prices as what predicted by noise trader theory.

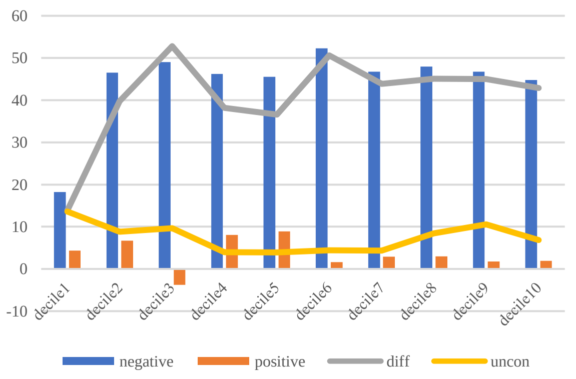
(a) T+1 Return Conditioned on Signs of Comp1 and Total Risk



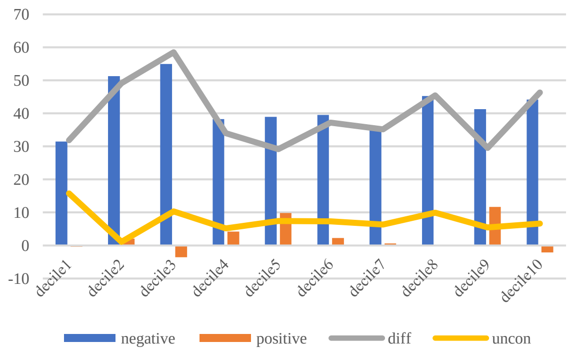
(b) T+1 Return Conditioned on Signs of Comp1 and Earnings



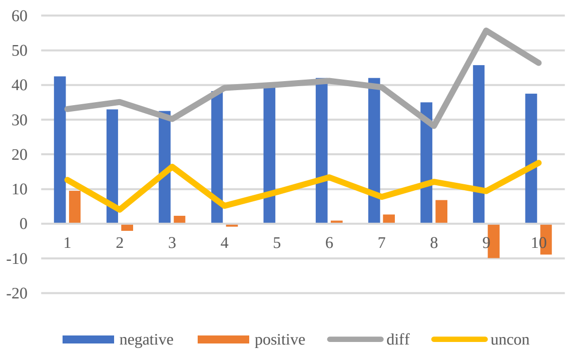
(c) T+1 Return Conditioned on Signs of Comp1 and Size



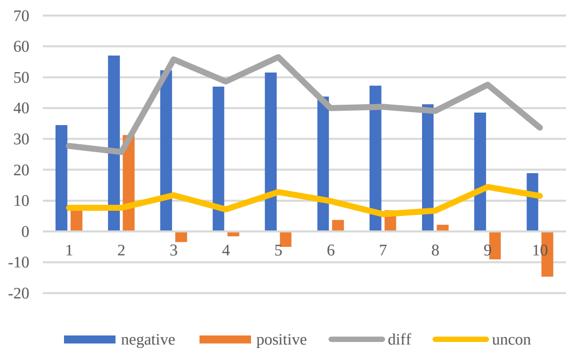
(d) T+1 Return Conditioned on Signs of Comp1 and Dividend Payout



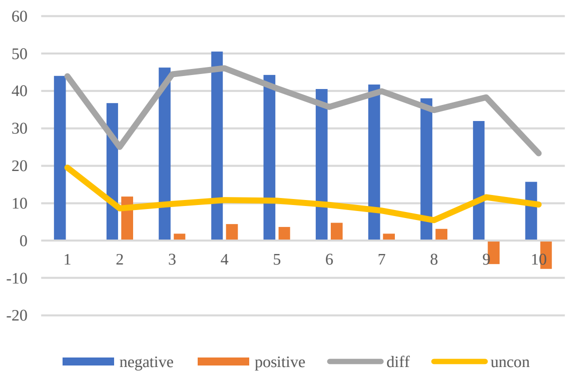
(e) T+1 Return Conditioned on Signs of Comp1 and Tangibility



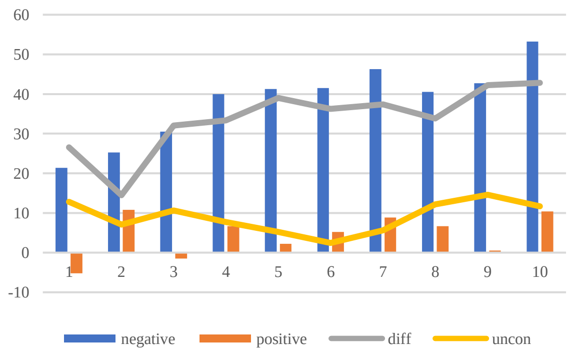
(f) T+1 Return Conditioned on Signs of Comp1 and R&D Expenses



(g) T+1 Return Conditioned on Signs of Comp1 and BE/ME



(h) T+1 Return Conditioned on Signs of Comp1 and Sales Growth



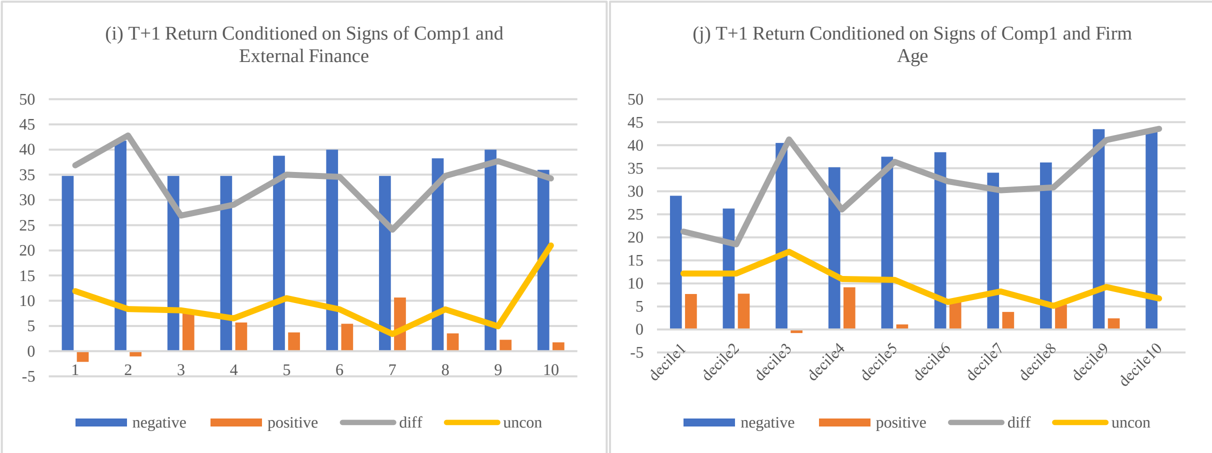


Figure 4-4 T+1 Portfolio Returns Sorted by Characteristics and Conditioned on Signs of Comp1

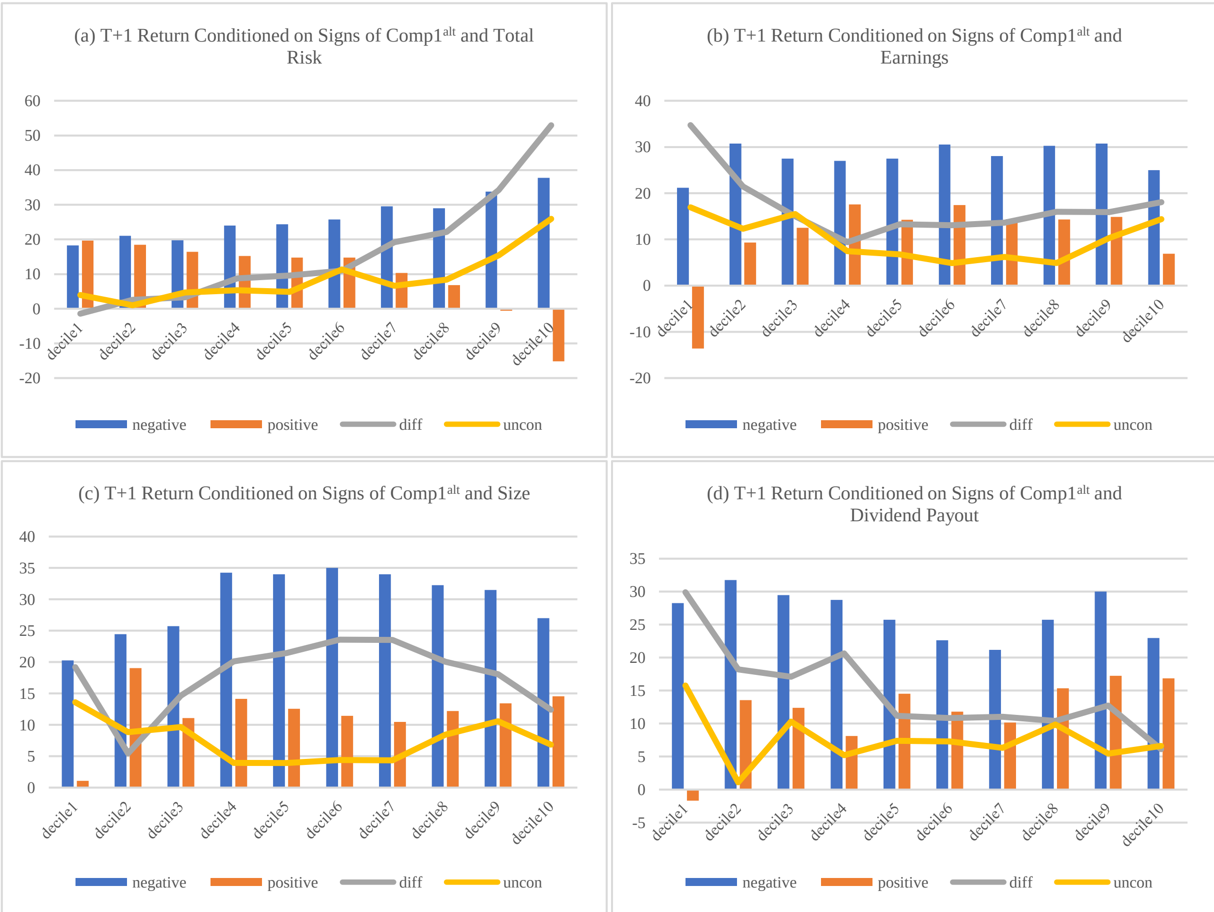


Figure 4-5 T+1 Portfolio Returns Sorted by Characteristics and Conditioned on Signs of Comp1^{alt}

4.3.4 Dynamic Analysis

Section 4.4.3.3 shows the t+1 price impact of the two sentiment proxies and I conduct an extensive investigation into the characteristic effects. However, the approach could be more dynamic in nature. I am curious to extend the horizon beyond one day. In addition, although Comp1^{alt} was not intended for a substitute for Comp1, it is necessary to bring them into a controlled environment. Even if they all include the same market wide sentiment component and have similar price impact as suggested in 4.3.2 and 4.3.3, one could still subsume the other. Controlling for each other helps to solve endogeneity issue. Another issue is the correlation between flow and performance. Established researches in mutual funds have documented a significant correlation of flows and recent (index and fund) performances. The instances includes but are not limited to Warther (1995), Lynch and Musto (2003), Huang, Wei and Yan (2007), Barber, Huang and Odean (2016). Although academics are yet to settle on its explanations, the correlation needs to be accounted for in our study since Comp1 is extracted from the flows. I need to prove that the future price impacts are from Comp1 itself, instead of the average flows.

In this section, I construct a system of regressions including the returns, flows and the sentiment proxies. The system is similar to VAR and hence is dynamic. The specification of the regression is:

Equation 11

$$\boldsymbol{Ret_{t+j}} = c_j + \sum_{t-k}^{t} \beta_k Ret_t + \gamma \overline{Flow}_t + \lambda_1 Comp1_t + \lambda_2 Comp1^{alt} + \epsilon_j$$

,where Ret$_{t+j}$ is a j*1 vector of S&P 500 Index returns; $\sum_{t-k}^{t} \beta_k Ret_t$, the lagged index returns for the past k days, is to control for return autocorrelation for up to k days; $\overline{Flow}_t$ is the equal weighted average flows of all leveraged funds in sample used in Table 4-6; Comp1^{alt} is not only a benchmark for Comp1, but also a control for all endogenous market conditions like surge in VIX and flight to heaven. For parsimony and to avoid multicollinearity, I do not include these variables altogether but the Comp1^{alt} only. The specification is similar but not identical to Da, Engelberg and Gao (2015). As a precaution for heteroscedasticity, the white standard error ϵ_j are reported. I set j=8 so the system allows for examination of price impact up to 8 days into the future.

Table 4-10 shows the result of the dynamic regression. The first column indicates a significant day 0 effect of sentiment, with coefficient of both Comp1 and Comp1^{alt} negative and significant. The intuition is that when contemporary sentiment is bearish, asset should be priced down due to overwhelming pessimism. Given the standard deviations of Comp1 and Comp1^{alt} are around 2 while the daily standard deviation of S&P 500 return is 0.008, change of one standard deviation in these sentiment proxies would correspond to 0.15~0.40 standard deviation changes in the return of the same day. This is economically large. It is also important to know that the two sentiment measures are both significant, indicating a uniqueness in Comp1 apart from market wide sentiment as proxied by Comp1^{alt}. Looking down the column, I find no significant effect from mean leveraged fund flows, although the coefficient is relatively large and positive. Warther (1995) documents a contemporaneous monthly impact of 0.52%, or 0.018% daily, half of what I have found. The difference is they use aggregate flows of all funds while I use flows of only leverage funds. After controlling for other variable, there seems to be no autocorrelations in returns left, judging from the non-significant coefficients on lagged returns. Nearly 13% of daily returns are explained by these variables.

Table 4-10 Regression of contemporary/future S&P 500 returns

	ret	ret(t+1)	ret(t+2)	ret(t+3)	ret(t+4)	ret(t+5)	ret(t+6)	ret(t+7)	ret(t+8)
Comp1	**-0.0007***	-0.0001	**0.0007***	0.0001	**0.0006***	0.0005	0.0002	-0.0001	0.0001
	(0.04)	(0.75)	(0.04)	(0.76)	(0.05)	(0.17)	(0.63)	(0.75)	(0.71)
Comp1^{alt}	**-0.0018*****	-0.0003	0	0	-0.0001	-0.0003	-0.0002	0.0004	-0.0002
	(0.00)	(0.51)	(0.98)	(0.95)	(0.74)	(0.42)	(0.71)	(0.39)	(0.58)
$\overline{Flow}$	0.0379	0.026	0.1666	0.1239	-0.0749	0.1224	-0.1263	0.0364	-0.0692
	(0.75)	(0.87)	(0.19)	(0.35)	(0.52)	(0.32)	(0.29)	(0.78)	(0.55)
ret(t-1)	-0.0154	0.061	-0.0854	-0.1533	-0.0328	-0.0795	-0.0091	0.0549	0.0359
	(0.82)	(0.44)	(0.24)	(0.05)	(0.66)	(0.33)	(0.90)	(0.46)	(0.66)
ret(t-2)	0.0644	-0.0174	**-0.2158***	-0.0695	-0.0929	-0.0453	0.05	0.0805	0.1072
	(0.42)	(0.82)	(0.01)	(0.44)	(0.23)	(0.55)	(0.48)	(0.36)	(0.17)
ret(t-3)	-0.0474	**-0.1527***	-0.1018	-0.0062	-0.125	0.0105	-0.0148	0.1453	-0.0128
	(0.57)	(0.05)	(0.21)	(0.94)	(0.07)	(0.90)	(0.88)	(0.07)	(0.89)
ret		-0.0593	0.0879	-0.1162	-0.1216	-0.06	-0.0689	-0.0069	0.0437
		(0.43)	(0.28)	(0.13)	(0.11)	(0.42)	(0.40)	(0.93)	(0.53)
constant	0.0007	0.0006	**0.0012***	0.0008	**0.0014***	0.0008	0.0006	0.0007	0.0008
	(0.17)	(0.34)	(0.04)	(0.16)	(0.01)	(0.19)	(0.30)	(0.23)	(0.22)
R^2 (Adjusted)	12.91%	3.69%	6.59%	4.85%	4.25%	3.35%	1.71%	2.58%	2.56%
N	240	238	239	238	239	237	236	236	236

The table shows time series OLS regression of S&P 500 Returns on component, flows and past returns. Flow is weighted average flows of all leveraged funds in sample. Individual flows are winsorized at 1% level. White Heteroscedasticity Robust standard errors are reported in parenthesis. ***, and * indicates significance at 99% and 95% level.

Looking horizontally, the t+1 impact of Comp1 and Comp1^{alt} are still negative but not significant, suggesting a weak lingering effect of sentiment in a daily scale. Theoretically, it is supported by the DSSW model by which noise traders earn higher expected returns in the short term because of their presence. There is some evidence of endogenous price reversion as return is negatively correlated with four-day lagged return (Column 3 confirms this as well). The t+2 column shows a price reversion in terms of Comp1, but not Comp1^{alt}. The coefficient on Comp1 is 0.0007, the same magnitude as the day0 effect. The Coefficient on Comp1 on t+4 is still significant at 0.0006, while the positive price reversals extend well into t+7. The coefficient on Comp1^{alt} is nearly zero at t+2 and never significant after day 0. It is surprising that a component extracted from leveraged fund flows has greater sentiment-like price implication than a component extracted from market variables. This suggest that the leveraged fund flows are strongly influenced by the market wide sentiment. While I never know whether the sentiment measured in Comp1 comes directly from the traders of leveraged funds, it subsumes the effects of Comp1^{alt}, an instrument I have chosen to partly solve the endogeneity issues. As Comp1 has strong and opposite correlations to both bull funds and bear funds, apparently the traders are fond of trading on sentiment shifts in the market, although I do not know exactly their profit and gains during the process and what rule they follow to account for these sentiment shifts.

4.4 Discussions and Conclusions

The empirical results show sentiment is a strong component in leveraged fund flows. Higher value of the components coincides with an outflow from bear funds and inflow into bull funds. As Comp1 and Comp1^{alt} is negatively correlated, investors act as if they are contrarian to market sentiment. These behaviours are not expected from our description of the leveraged funds. If leveraged funds do act as “gambles” on stock returns, its investors should assumedly be naïve and unsophisticated, in a way that their trade will be (positively) sensitive to market sentiment. Indeed, our perception of these investors may be wrong at the very first. An alternative hypothesis is that leveraged fund investors are there because they are sophisticated investors who know exactly what the market will be doing, otherwise the high risk of these funds will have kept them outside. These investors may hold exclusive information on intrinsic value of stocks or are aware of the current sentiment condition. When the market sentiment is high/low, they know the stocks are valued above/below fundamental and return will reverse after some period and purchase bear/bull fund to secure the profit. Whether fund investors are “smart” or “dumb” money has always been a hard question and academics are yet to settle on this topic. For example, Gruber (1996) and Zheng (1999) finds that investors channel money into funds that subsequently performed well. However Sapp and Tiwari (2004) confronted that their results are distorted by price momentum. Frazzini and Lamont (2008) warns that fund investors reduce their wealth in the long run. They proved that flows are dumb money by allocating to funds that invest in stocks with lower future returns.

I did a brief test on this issue. If leveraged fund investors are smart money, one should expect that bull flows predicts higher returns and bear flows predicts lower returns. The sophisticated timing strategy should be able to earn them a positive abnormal return relative to the market. To reveal the dynamics between sentiment, flows and returns, I construct a VAR system containing Comp1, Comp1^{alt}, value weighted mean bull and bear fund flows and CRSP Total Market Index Returns. Based on Akaike Information Criterion, I select an optimal lag of 3. The result (presented in Table 4-11) does not support that leveraged fund investors are smart money. In the fourth column, the flows and sentiment measures barely predict index return. The adjusted R Squared for the index return equation is negative and the F-stat suggest it is an invalid model as well. The negative adjusted R Squared is due to the random walk property of short term returns. Technically I cannot predict a random walk using a set of irrelevant information (as is the fourth model). Theoretically, bull flows should be related to higher future returns. In our case, bull flows from t-1 and t-2 has a negative relationship with future index returns, but the t-stat is not significant. The only significant coefficient in Column 4 is the bear flow at t-2, which should have been positive. Despite their sentiment contrarian strategy, leveraged fund investors do not time the market well, at least using our benchmark. An additional Granger causality test reveals that neither variables Granger cause index returns. Given that our sample do not contain sector funds, their directional bet on the market itself may have been wrong in average. In reality, the hefty fees on these funds will add to their losses. I do find some valuable information inTable 4-11. For example, I find that Comp1 and Comp1^{alt} have a reciprocal causality. This means the sentiment in leveraged fund market and equity market do not perfectly synchronize. There is some spillover effect among these markets. Previous studies have discovered sentiment spillover at both spatial (Tsai, 2014) and chronological (Hansda and Ray, 2003) level. Although this is not the primary objective of this study, I encourage further investigation into this issue.

Table 4-11 Vector Auto Regression Model of Sentiment, Return and Flows

Sample: 5/07/2012 5/08/2013 (188 observations)

	COMP1_^{ALT}	BULLFLOW	BEARFLOW	INDEX_RETURN	COMP1
COMP1_^{ALT}(-1)	**0.521**	0.000	**-0.002**	0.000	-0.005
	5.431	-0.402	-2.425	0.093	-0.030
COMP1_^{ALT}(-2)	**0.269**	0.001	0.000	0.000	-0.032
	2.609	1.445	-0.070	0.130	-0.190
COMP1_^{ALT}(-3)	0.123	-0.001	0.001	0.000	0.044
	1.290	-0.864	1.427	-0.064	0.278
BULLFLOW(-1)	14.467	0.107	-0.047	-0.067	**-30.534**
	1.412	1.336	-0.586	-0.594	-1.801
BULLFLOW(-2)	2.819	-0.138	-0.076	-0.126	**37.701**
	0.277	**-1.737**	-0.959	-1.123	2.239
BULLFLOW(-3)	-1.146	-0.063	-0.002	0.083	**-53.784**
	-0.113	-0.797	-0.024	0.750	-3.213
BEARFLOW(-1)	-2.549	-0.070	0.110	-0.043	10.978
	-0.241	-0.840	1.334	-0.372	0.626
BEARFLOW(-2)	-8.455	-0.106	0.022	**0.246**	-1.033
	-0.789	-1.263	0.268	2.087	-0.058
BEARFLOW(-3)	-0.208	**-0.212**	0.075	-0.013	25.233
	-0.019	-2.521	0.902	-0.113	1.420
INDEX_RETURN(-1)	-5.992	-0.083	**-0.136**	0.014	**51.643**
	-0.659	-1.170	-1.928	0.138	3.432
INDEX_RETURN(-2)	-11.389	0.027	0.045	0.079	**64.573**
	-1.276	0.393	0.643	0.809	4.373
INDEX_RETURN(-3)	-13.388	-0.100	**0.106**	0.138	**86.120**
	-1.627	-1.556	1.660	1.523	6.326
COMP1(-1)	**0.082**	0.000	0.000	-0.001	**0.232**
	1.811	-0.961	-0.602	-1.239	3.110
COMP1(-2)	0.047	0.000	0.000	-0.001	0.108
	1.036	-0.735	0.472	-1.173	1.444
COMP1(-3)	**-0.080**	0.000	0.000	0.001	0.096
	-1.880	-0.115	0.782	1.356	1.366
R2 (adjsuted)	0.747	0.153	0.109	-0.027	0.566
F-Stat	37.786	3.243	2.524	0.674	17.235

The table reports VAR (3) model for components, flows and index returns. Lag is optimal by referring to Akaike information criterion. Flows are weighted average flows of all leveraged funds in sample. Individual flows are winsorized at 1%. Bear funds refers to any leveraged funds with objective of inversely tracking an index and bull funds refers to the opposite. The index used is CRSP Total Market Index. All series has passed ADF unit root test. Bold text indicates significance at 90% level.

Our study is limited to its sample size, since I do not have further subscription to the database. In fact, it is a common issues in many fund studies using daily data (Goetzmann, William N.; Massa, Massimo, Rouwenhorst (2000); Brown *et al.* (2003); Ben-Rephael, Kandel and Wohl (2011)). A more meaningful study for sentiment should reveal a long-term picture. Due to the limited transparency of fund management companies on their daily portfolio holdings (the minimal frequency requirement for net asset disclosure in US is quarterly which is not suited for studies on leveraged funds), I are yet to see a more comprehensive study on sentiment in leveraged fund market. The quality of the study is directly related to quality of the data. Da, Engelberg and Gao (2015) has one but their primary focus is not leveraged funds and their methodology is not identical to ours. As the development of leveraged funds, I do hope data of higher qualities and length will be available.

Our study may have special bearings for the regulators of leveraged funds. As the flows of these funds are heavily influenced by sentiment, do we need more entry requirement for these products? Are these funds too pricy and do investors not warned enough? There are indeed actions from regulators. For example, SEC has never approved 4x leveraged funds in the past and Financial Industry Regulatory Authority (FINRA) announces several cases of inappropriate sales of these complex and leveraged products. In 2016, they propose a rule to limit usage of derivative and leverage in mutual funds. However, several 4x leveraged funds are given green light in 2017, signaling the potential death of the proposal. After all, the mere existence of leveraged funds, especially ones with a daily target, is questionable. It is too complex and risky for broad investors, with literally zero help on their understandings on healthy investment. The detriments can be seen from a recent case. At the start of 2018, the XIV, an inverse geared funds on the CBOE VIX volatility index, are one of the most favored trades in Wall Street as the US stock market continues its eight-year long rally from the 2008 crisis. Investors believe that the market will continue its momentum while VIX stays calm and low. However, in 5 February 2018, there was a major selloff in stock market and VIX soars to one of the highest level in history. As a result, price of XIV dropped nearly 90% in one day. The product come to its demise in 20 February as Credit Suiss announced its termination. From our perspective, events like this should always be avoided. However, I can do more than simply ban them as it is against a free and innovative market. I urge issuers of these products to conduct more investor education and refine their products. Many companies do. For example, there are more and more leveraged funds which do not target daily return anymore. Instead, they begin to target monthly or even quarterly returns, a better balance between innovation and risk management.

Chapter 5 - CONCLUSIONS

In this thesis, the primary research instrument is a convenient workhorse of consumer investments – the open-end mutual fund flows. Such funds fulfil the purchase and redemption decisions of investors, which are called the inflows and outflows. The size of the fund will either shrink or expand due to these investment flows, resulting to change in the revenue of fund managers. Study on the investment flows spans various topics, such as investor beliefs about the quality of the fund's management, the fund's security trades arising from investor money flows, investment decisions by the fund's manager, the resultant market prices of traded securities, and the revenue earned by the fund's investment advisors.

The study puts significant emphasis on the interaction between investment flows and performance – either the performance of the underlying fund or other assets. Their interactions provide a rich environment for economic research because they reveal the actual decisions of consumers facing changing economic conditions and how they may evaluate the inherent quality of the managers. While previous literature has found a strong concurrent relationship between flows and performance, it remains unclear what this relationship stand for, and what implication can be derived. The literature is also unsettled on the rationality of the flows. Do flows correctly act upon economic signal from several fund specific characteristics, such as fee revisions, managerial altenations and track records, or macro conditions like broad market return and market-wide swings of sentiment? This is important because the rationality of flows determine whether they are market stabilizing or unstablizing, or whether investors increase long term wealth from their mutual fund investments.

The second chapter is not only the prelude for our flow-performance study, but also answer to a simple but often ignored question: whats the true performance of fund investors and how performance vary within investor groups? The chapter acknowledges that there are three key aspects to outcome of a fund investment process: fund selection, timing and fee choice and argue that the three aspects are all material determinants of a successful investment process.

The study is based on several established papers on flow-performance relationships in mutual fund market. Warther (1995) is a pioneer paper that discovers a significant correlation between flows and performance. Sirri and Tufano (1998) discovers a convex-shaped flow-performance function and attributes the cause to asymmetrical information. Berk and Green (2004) established a model in which investors trade against good performers and against bad performers but funds themselves suffer from diseconomy of scale. As the fund change in size, it deviates from optimal portfolio size and result to better or worse performance. Huang, Wei and Yan (2012) argues that flow-performance sensitivity is a rational investor learning process. Based on their arguments, I obtain a simple but effective proxy for investor sophistication: the sensitivity of flows to recent (abnormal) performances. To granularly measure their respective performance, I decompose their performance into three aspects: abnormal returns, fees and timings, a scheme proposed in Fama (1972). The abnormal return is alpha on a four-factor model, which is a traditional before fee, relative measure of whether a fund has beat the market. Fee selection takes into account the average fees that jeopardize the performance and timing cost is measured by “performance gap”, a concept used in Nesbitt (1995); Dichev (2007); Friesen and Sapp (2007); Bullard, Friesen and Sapp (2008). The result is that sophisticated investors earn higher risk adjusted returns and avoid high fees. In addition, investors’ timing performance can be greatly improved by trading less, with the most significant improvements seen on most sophisticated investors.

One of the key implication in this chapter is that sophistication of investors (at least for mutual funds) are multi-dimensional. Traditional literature tends to define sophistication based on whether an agent has beaten the market, or equivalently, the magnitude of their abnormal return in terms of some risk benchmarks. The other two aspects, timing and fees, are less discussed on or treated as isolated subjects. We can see in chapter two that investors that are capable of selecting better managers are not necessarily ones capable of timing the market well nor good at cost control. While the chapter is a preliminary research into this issue, I suggest future work to be conducted on the interaction of the three abilities. For example, what is the relationship between timing and fee? Do aggressive market timers choose low-fee low-load funds to facilitate their high turnovers? What causes the mismatch of good fund pickers and good market timers? Are they institutional, contractual or behavioural? How can we replicate and explain the sophistication measure proposed in the chapter, using observed characteristics, albeit bound to be cruder? The questions are uniquely easier to be dealt with in mutual fund field thanks to the existence of flows. It is hard to find equivalents in stock research. However, to achieve those goals, more granular and comprehensive datasets are required.

The regulatory implicate of chapter two is that we should not only focus on the quality control of funds, but also the pricing for the mutual fund service (fees) and investor educations. As of now, the pricing of the mutual funds has been fully marketized. Investors are left to screen through thousands of products with different price, with their inherient quality not immediately available. Others choose to delegate to brookers. This often cause funds with high fees and low quality to survive longer than usual. There should be more action to lower the search cost of investors, or to motivate managers with reasonable incentives and to punish brookers for misconduct using information asymmetry. As for timing, we should inform investors of the potential loss/gain in long term wealth if they choose a specific turnover, and how their current turnovers are healthy or not. As the mutual fund market develops, many investors realize that timing the market may not be a cost-efficient way to participate. The expansing in low cost ETFs in recent years is a proof. However it is still not enough.

The research question in third chapter is: is there a calendar effect for flow-performance relationship? Does the shape of the function change across the months and what drives the change? The study fills the gap by emphasizing several exogeneous factor of flow-return relationship such as portfolio rebalance and tax-loss selling which interact with calendar dates. Previous literature commonly finds a convex function. Chevalier and Ellison (1997) is first to document the convexity and they argue the convexity may incentivize agency problems. Sirri and Tufano (1998) explained using information search cost and Lynch and

Musto (2003) explained with survivalship bias of mutual fund strategies. However, all the study examines only average shape of the flow-performance function. None of them attempt to tackle calendar effect. Calendar effect is potentially a strong determinant of flow-performance relationship. Factors such as tax-loss selling (Constantinides 1983), portfolio rebalance, disposition effect (Kaustia 2011)) and seasonal variation in risk appetite (Kamstra *et al.* 2017) may interact with dates and change the flow-performance relationship. In this study, I conduct a similar flow-performance regression for each month. The regression is piecewise which separates the sensitivity of mutual fund flows to returns into five parts. I also construct a concise measure of whether a group of funds are bought or sold at any time during the year to disentangle several confounding effects. I find that the shape of the function does change throughout the year and they are affected by tax-loss selling and portfolio rebalance.

The study provides new inspirations to extant literature on the non-linearity of flow-performance function. While several papers explore possible explanation on this non-linearity, they either focus on characteristic of the fund or scenarios in which manager's incentives misalign with cosumers objectives. In other aspects, these investigation rarely involve the role of calendar effect. In this chapter, I provide a simple explanation that calendar effect of flows may have caused this non-linearity, because several factors that interact with calendar months alter the behaviors of inflows and outflows differently. In my case, the factors are tax-loss selling and portfolio rebalance. If we treat flows as evaluation processes for managers, then these two effects may alter these processes materially. In the real world where there are capital gain and distribution taxes, and where consumers periodically adjust their portfolios, track record of funds may not always represent quality of funds, but many more like tax overhang. This is a fact previous literature often overlook.

Due to several limitations, the chapter is far from perfect. One of them is dataset. For example, I did not gain access to detailed distribution and tax overhang data. Had I have access to them, I can explain whether the change in sensitivity of flow to performance is indeed caused by tax, rather than proxying them using fund returns. In addition, I have not found gross flow data that suits the required frequency and I doubt there will be one. I approximate the gross flows using cross-sectional data in this chapter (PGR, PLR, PS) but these measures are reliant on a large cross-section, and the idiosyncratic effect of these cross-sections will potentially distort or invalidate results.

The study can be expanded on three aspects. The first is whether disposition effect, a widely discussed topic in decising making, plays a part in the non-linearity of flow-performance relationship. Disposition effect is a natural candidate for causing non-linearity, since investors are described as selling winners too early and holding on to losers for too long. Arguably, if fund investors do suffer from disposition effect, they will treat winning funds differently than losing funds. The muted sensitivity of flows to bad performance region may be a result of them to be reluctant to sell these funds. This is tricky task since we would need to measure the extent to which investors suffer from disposition effect, or finding a proxy for it. An experiment design would be suitable for study of this sort. Another is whether the shifts in flow-performance relationship are related to seasonal asset allocation discussed in Kamstra *et al.* (2017). Kamstra *et al.* (2017) finds that Seasonal Effective Disorder significantly alter the risk appetite of investors within a year. Investors are found to be risk averse in autumn and relatively risk seeking in spring. This is similar to my result in which investors are more risk seeking and contrarian at turn of the year. The third aspect is whether the shift in flow-performance relationship I find is related to January effect, a popular topic in equity study. Mutual fund flows has the power to affect security market indirectly. Previous literature document price pressure of fund flow at market level (Lou 2012) because mutual fund is taking a substantial share in US financial system. There are also paper on flows unstablizing the market due to fire sale (Coval and Stafford 2007) or irrationality of investors Frazzini and Lamont (2008). Given these relationships, it is reasonable to suspect that the large scale portfolio shift at end of the year may result to a price pattern very similar to January effect.

In fourth chapter, I focus on a special group of funds, the leveraged funds, which mainly caters for day traders. *The research question is whether their flows reflect market wide* *sentiment.* Leveraged funds are funds that allows investors to bet on daily performance of stock indexes with leverage and direction. As these funds track only daily index returns and investment horizon longer than one day will result to material deviation from index returns, these funds are unlikely used by mid- or long-term optimizers. As common study suggest too much trading can be harmful (Barber and Odean 2000), I notice that the flows for these funds may be sentiment driven. In this study, I obtain daily flows of nearly 100 largest leveraged funds trading in US and extract the first principal component from these funds. In addition, I follow Baker and Wurgler (2006a) to construct a daily sentiment index (the alternative sentiment measure) from several market variables, which are purposely chosen to be unrelated to fund markets. I find that the first component from leveraged funds is associated with investors' migration between bull and bear funds and it has strong correlation with our alternative daily sentiment measure. In a later test, the two sentiment measures have similar price impact as a hypothetical sentiment measure would have. I have also examined the limits of arbitrage effect proposed in Shleifer and Vishny (1997). The sentiment component predicts similar cross-section of price revision for up to 7 days into future.

This study is limited to its sample size, since I do not have further subscription to the database. In fact, it is a common issues in many fund studies using daily data (Goetzmann, William N.; Massa, Massimo, Rouwenhorst (2000); Brown *et al.* (2003); Ben-Rephael, Kandel and Wohl (2011)). A more meaningful study for sentiment should reveal a long-term picture. Due to the limited transparency of fund management companies on their daily portfolio holdings (the minimal frequency requirement for net asset disclosure in US is quarterly which is not suited for studies on leveraged funds), I am yet to see a more comprehensive study on sentiment in leveraged fund market. The quality of the study is directly related to quality of the data. Da, Engelberg and Gao (2015) has one but their primary focus is not leveraged funds and their methodology is not identical to ours. As the development of leveraged funds, I do hope data of higher qualities and length will be available.

This chapter may have special bearings for the regulators of leveraged funds. As the flows of these funds are heavily influenced by sentiment, do we need more entry requirement for these products? Are these funds too pricy and do investors not warned enough? There are indeed actions from regulators. For example, SEC has never approved 4x leveraged funds in the past and Financial Industry Regulatory Authority (FINRA) announces several cases of inappropriate sales of these complex and leveraged products. In 2016, they propose a rule to limit usage of derivative and leverage in mutual funds. However, several 4x leveraged funds are given green light in 2017, signaling the potential death of the proposal. After all, the mere existence of leveraged funds, especially ones with a daily target, is questionable. It is too complex and risky for broad investors, with literally zero help on their understandings on healthy investment. The detriments can be seen from a recent case. At the start of 2018, the XIV, an inverse geared funds on the CBOE VIX volatility index, are one of the most favored trades in Wall Street as the US stock market continues its eight-year long rally from the 2008 crisis. Investors believe that the market will continue its momentum while VIX stays calm and low. However, in 5 February 2018, there was a major selloff in stock market and VIX soars to one of the highest level in history. As a result, price of XIV dropped nearly 90% in one day. The product come to its demise in 20 February as Credit Suiss announced its termination. From our perspective, events like this should always be avoided. However, I can do more than simply ban them as it is against a free and innovative market. I urge issuers of these products to conduct more investor education and refine their products. Many companies do. For example, there are more and more leveraged funds which do not target daily return anymore. Instead, they begin to target monthly or even quarterly returns, a better balance between innovation and risk management.

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LIST OF ABBREVIATIONS

AAII	The American Association of Individual Investors
ADS Index	Aruoba-Diebold-Scotti Business Conditions Index
AUM	Asset Under Management
ATYPE	Asset Type
CAPM	Capital Asset Pricing Model
CAGR	Conpound Annual Growth Rate
CBOE	Chicago Board of Exchange
CRSP	The Center for Research in Security Prices
EPU Index	Economic Policy Uncertainty Index
EW	Equal Weighted
ETF	Exchange Traded Funds
EMH	Efficient Market Hypothesis
GDP	Gross Domestic Product
FEARS Index	Financial and Economic Attitudes Revealed by Search Index
ICI	Investment Company Institute
LGC	Lipper Global Classification
NCF	Net Cash Flow
OLS	Ordinary Least Square
PCA	Principal Component Analysis
PGR	Proportion of Gains Realized
PLR	Proportion of Losses Realized
PS	Probability of being Sold
TAAR	Timing Adjusted Abnrmal Return
TER	Total Expense Ratio
TFAAR	Timing and Fee Adjusted Abnormal Return
TRIN	Short-Term Trading Index
VW	Value Weighted
VOL	Volume