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A Review of Behavioural and Management Effects in Mutual Fund Performance

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Abstract:

This paper surveys and critically evaluates the literature on the role of management effects and fund characteristics in mutual fund performance. First, a brief overview of performance measures is provided. Second, empirical findings on the predictive power of fund characteristics in explaining future returns are discussed. Third, the paper reviews the literature on fund manager behavioural biases and the impact these have on risk taking and returns. Finally, the impact of organizational structure, governance and strategy on both fund risk taking and future performance is examined. While a number of surveys on mutual fund performance are available, these have not focused on the role of manager behavioural biases, manager characteristics and fund management strategic behavior on fund performance and risk taking. This review is an attempt to fill this gap. Empirical results indicate that finding successful funds *ex-ante* is extremely difficult, if not impossible. In contrast, there is strong evidence that poor performance persists for many of the prior "loser fractile" portfolios of funds. A number of manager behavioural biases are prevalent in the mutual fund industry and they generally detract from returns.

Keywords : Mutual fund performance, fund characteristics, manager characteristics, manager behavior biases.

JEL Classification: G11, G12, G14.

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1. INTRODUCTION

Mutual funds are pooled investments which provide liquidity and enable investors to enjoy economies of scale from low cost diversified portfolios which are often differentiated by fund styles such as aggressive growth, growth and income, growth, equity-income and small companies[1]. Most funds are 'active' in that they either try to pick 'winner stocks' or they engage in market timing (i.e. predicting relative returns of broad asset classes) and these managed funds generally charge higher fees than 'index' or 'tracker' funds (which mimic movements in broad market indexes)[2]. In the US and UK about 70% of institutional funds are actively managed and this rises to over 90% for retail funds.

As of 2014, total worldwide assets invested in mutual funds and exchange-traded funds was $33.4 trillion. US mutual fund total net assets was almost $16tn (Europe was $9.5tn, UK was $1.2tn) and 52% of this total was invested in equity (domestic and global). In the US, 53m households (43% of households, and 90m individuals) own mutual funds[3]. This extensive ownership of, and exposure to, mutual funds gives rise to considerable interest in mutual fund performance, not least in the academic literature.

The rationale for managed funds is that they "add value" by using private information and manager skill to produce "abnormal performance". Future fund performance may be influenced by fund characteristics (e.g. past performance, turnover, age of the fund, fees, fund flows, tracking error), compensation structures (e.g. incentive payments, extent of managerial ownership of the funds), fund manager characteristics (e.g. educational attainment, managerial tenure) and strategic considerations (e.g. manager change, board composition, mergers and acquisitions).

The extant literature around mutual fund performance may be classified as follows. First, there is a large volume of work focused on performance evaluation of funds including performance persistence, market timing and volatility timing.

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[1] In the UK mutual funds are often referred to as Unit Trusts although their correct designation is Open Ended Investment Companies, OEIC. In the US 'unit trusts' purchase assets but do not subsequently trade them. In the US 'self-declared' fund styles are overseen by the SEC but it is not always the case that the style name accurately represents the underlying assets in the portfolio. The SEC rules mandate that a fund name must imply that it has at least 80% of its assets in securities of this type/name but there is much leeway in interpretation of the rule. Morningstar, the Thompson/CDA-Spectrum files and the CRSP mutual fund files have somewhat different investment categories from each other – so allocation to a particular category requires some judgment – Wermers (2003). We use the terms 'category' and 'style' interchangeably.

[2] With the recent appearance of Exchange Traded Funds (ETFs), investors may also 'track' a diversified position in a given style category (e.g. small stocks, telecom stocks). ETFs are also redeemable at market value at any time of the trading day (not just at 4pm New York time as for US mutual funds) and ETFs often have special tax privileges.

Second, cross-sectional evidence on the relation between fund performance and fund characteristics has also received attention. In particular, recent studies have examined the impact on fund performance of fund attributes such as fund flow, active share, industrial concentration, fund size, industry size, turnover, commonality in stock holdings, manager compensation structures, competitive pressures and discretionary versus liquidity trading.

Third, is the impact of behavioural effects on fund performance and manager risk taking. Behavioural finance recognises that investor psychological biases often lead to practices that deviate from those predicted by rational models. Key manager behavioural patterns include excessive trading, overconfidence, a disposition effect, herding, window dressing, risk taking and home bias - while behavior patterns also arise due to career concerns (e.g. employment risk), fund ownership structure and performance related incentive fees.

Finally, the mutual fund literature looks at the impact on performance of fund management company (FMC) governance and culture, organisational structure and strategy. Organisational structure can bestow benefits on funds. For example, being part of a fund family allows funds to enjoy economies of scale in advertising, and also allows FMCs to strategically shift investment opportunities (e.g. IPOs) or risk, between funds. Further governance, structure and strategy topics that arise in the literature include fiduciary responsibility and stewardship, corporate culture, fund families, mergers and acquisitions, affiliated funds of funds and fund incubation. We review this literature and its impact on fund performance and risk taking.

There are a number of comprehensive review articles covering the choice of performance models and whether active management adds value[4]. However, to our knowledge there has been no comprehensive review undertaken of either studies of the impact of manager behavioural effects or of mutual fund organisational structure and governance on fund performance.

In a seminal article, Grossman and Stiglitz (1980) argue that in equilibrium, expected abnormal returns should *not* be zero, otherwise there would be no incentive to gather and process costly information. Taking up the idea that information processing is costly, Berk and Green (2004) use a general equilibrium competitive model to analyze fund flows, *ex-post* returns and performance persistence. Fund managers have a differential skill[5] (e.g. stock picking ability) at a *gross* return level, so they can earn a return (before fees) in excess of a passive benchmark. True managerial skill is unobservable by investors but investors try to infer skill from past returns

[3] Statistics taken from Investment Company Institute 2015.
[4] See for example, Wermers (2011), Cuthbertson, Nitzsche and O'Sullivan (2010), Ferson (2012), Cremers, Petajisto and Zitzewitz (2013), Lehmann and Timmermann (2007) and Wermers (2011).

(which comprises true unobservable skill and luck/noise). High prior return funds attract disproportionate cash inflows (which are infinitely elastic) and funds are subject to diminishing returns. So past high return funds expand until the marginal dollar is invested by managers in index (passive) funds, since any successful stock picking is now impossible (because bid-ask spreads widen and anomalies have been arbitraged away).

Highly skilled managers manage large funds and hence earn high fee revenues based on a fixed percentage of assets under management (AUM) – this is how skilled managers extract their rents. It is rational for investors to chase high past returns but in so doing they (immediately) reduce expectations of future after-fee net returns to zero. Hence, investors *expect* to earn zero net returns in equilibrium and past returns cannot be used *ex-ante* by investors to predict future performance in real time[6].

However, two key questions arise. First, how long does any disequilibrium and hence (good or bad) abnormal performance last? Second, is abnormal performance economically significant and exploitable by either fund managers or investors.

The main aim of this paper is to provide a critical review of empirical findings on the determinants of future fund performance, concentrating on fund characteristics, manager behavioural biases and mutual fund company structure, governance and strategies. We focus our review on US and UK studies published in the literature over the last 15 years where innovation and data advances have been most marked.

The rest of the article is structured as follows. Section 2 provides a brief overview of fund performance measures as well as methodology in testing performance predictability. Section 3 discusses the empirical findings around the relation between fund characteristics and future performance. The literature on the impact of fund manager behavioural effects on fund performance and risk raking is reviewed in section 4 while in section 5 we analyze the impact of

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[5] Fund returns have a fixed (unobservable) component and a noise component, $R_{i,t} = \alpha_i + \varepsilon_{i,t}$.

[6] As Pastor, Stambaugh and Taylor (2014) note a lack of *ex-ante* predictability by investors in real time, does not rule out a correlation between fund characteristics (e.g. size) and future performance, when using a regression on historical data. Hence, the Berk and Green (2004) model does not rule out *ex-post* predictability in the historical data. If the true relationship between fund return $R_{i,t}$ and size $X_{i,t-1}$ is $R_{i,t} = \alpha_i + \delta_i X_{i,t-1} + \varepsilon_{i,t}$ then the expected return as perceived by investors is $E_{t-1}R_{i,t} = \alpha_i + \delta_i X_{i,t-1}$. At time t-1, investors know $\delta_i X_{i,t-1}$ but the fund-specific skill of the manager is unobservable and unknown to the investor. Hence $E_{t-1}R_{i,t}$ is also not known by the investor. In the model the investors' changing perceptions of $E_{t-1}R_{i,t}$ based on past returns leads to endogenous future inflows and outflows of cash, and hence to changes in the size of the fund.

fund management company governance, organisational structure and strategy on performance and risk taking. Conclusions are presented in Section 6.

2. PERFORMANCE MEASURES

There are typically two methodologic approaches to measuring the impact of fund characteristics on future performance: a multivariate regression approach and a recursive portfolio sorting approach. In the first, either a Fama-MacBeth (1973) cross-section rolling regression or a panel data approach is used. In the second, funds are typically sorted into fractiles (e.g. deciles) based on an attribute under examination, and periodically rebalanced. Post-sort returns are then used to assess future performance. Fund manager performance is usually measured by *gross fund returns*[7] while investors earn *net returns* (i.e. gross returns after deduction of fund management fees)[8].

Having identified predictors of future performance in a multivariate framework, a key question is whether this information can be used to implement an *ex-ante* strategy in real time which produces positive performance in the future. Investors may dynamically re-allocate their savings towards future 'winner funds', and hence "money may be smart". Net returns to investors must outweigh any switching costs between funds – these include search costs, load fees, administrative and advisory fees. As the number of possible rules for predicting fund returns is very large, issues of data mining and data snooping come to the fore.

To retain consistency across various studies we mainly report fund performance either as the excess benchmark return $r_p - r_b$ or as the alpha from a specific factor model[9]. If $f_{t+1} = \{ f_{1t+1}, f_{2t+1}, ... \quad , f_{kt+1}\}'$ are the k-factors that determine stock returns and $\beta^{'}_{jt} = \{\beta_{j1}, \beta_{j2}, ... \quad , \beta_{j,k}\}$ are the k-factor loadings, then a mutual fund-*p* at time *t*, with asset proportions $w_{j,t}$ (j = 1, 2, …, m) has a required return (to compensate for factor risk) equal to $\beta^{'}_{p,t} E(f_{t+1} \mid I_t)$ and the fund abnormal performance is given by α_{pt} in the regression (Jensen1968, Lehmann and Modest 1987):

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7 After transactions costs of buying and selling securities

8 Net returns exclude any load fees and any income or capital gains taxes applicable to the individual investor.

9 Another widely used performance metric is the characteristic selectivity CS measure (Daniel at al. 1997) which often gives similar qualitative results to 4F-alpha measures.

[1] $$r^{*}_{pt+1} = \sum_{j=1}^{P}(w_{jt}\alpha_{jt} + w_{jt}\beta'_{jt})\, f_{t+1} + \sum_{j=1}^{P} w_{jt}\varepsilon_{jt+1} = \alpha_{pt} + \beta'_{pt} f_{t+1} + \varepsilon_{pt+1}$$

where $\varepsilon_{pt} = \sum_{j=1}^{p} w_{jt}\varepsilon_{jt}$, $\alpha_{pt} = \sum_{j=1}^{P}(w_{jt}\alpha_{jt})$, $\beta_{pt} = \sum_{j=1}^{P}(w_{jt}\beta_{jt})$. The dependent variable $r^{*}_{p,t+1}$ is usually the fund return r_{pt+1} relative to the risk-free rate $(r_p - r)$, or the fund return relative to a chosen benchmark return, $(r_p - r_b)$. Note that the fund's parameters will be time varying if either the factor betas or the fund weights are time varying. Time variation in factor loadings in the empirical literature has been examined using rolling regressions, loadings depending on observable (macro) variables, switching models and time-varying parameter models based on unobservable factors (Kalman filter).

Style Approach

Practitioners using factor models probably interpret the alpha of the 4F model primarily in terms of "outperformance" relative to mechanical "style factors" that could easily be implemented by individual investors themselves (Sharpe 1992). If investors can replicate (or construct) exposure to passive factors (e.g. return on the S&P500) they can themselves earn an expected return of $\beta'_{pt} E f_{t+1}$.

A positive 4F-alpha, (net of management fees) for an actively managed fund then implies superior skill over the passive replication portfolio directly available to the investor. Ideally, the passive factors should represent tradable assets with returns measured net of any costs payable by the investor (e.g. returns to ETFs which are net of any management and administrative fees). If the factors are not tradable then their returns should be adjusted for the full cost of replicating the factors. In this approach the "style factors" need not represent systematic economic risk but must be replicable by the investor.

Unconditional Models

Empirical studies often assume factor loadings are time invariant and estimate *unconditional* factor models, one of the most popular being Carhart's (1997) four factor (4F) model:

[2] $$r_{pt+1} = \alpha_p + \beta_{1p} r_{m,t+1} + \beta_{2p} SMB_{t+1} + \beta_{3p} HML_{t+1} + \beta_{4p} MOM_{t+1} + \varepsilon_{pt+1}$$

where r_m is the excess return on the market portfolio, SMB, HML and MOM are zero investment factor mimicking portfolios for size, book-to-market value and momentum effects respectively. If $\beta_{4p} = 0$ the model is the Fama-French (1993) 3F model while Jensen's (1968) alpha is the intercept from the CAPM one-factor (or market) model using only $r_{m,t+1}$. Note that the Fama-French factors are not tradeable assets and therefore in the "style factor" approach their returns should be measured net of any costs of replication.

Conditional Models

To mitigate the problem of separating the impact on fund returns of skill based on private information from that due to publicly available (macro) information Z_t, the Fama-French model is augmented to give:

[3] $$r_{p,t+1} = \alpha_{0p} + a_p^{'} z_t + b_{0p} f_{m,t+1} + b_{1p}^{'} (z_t * f_{m,t+1}) + \varepsilon_{p,t+1}$$

where $z_t = Z_t - EZ_t$ (Ferson and Schadt 1996, Christopherson, Ferson and Glassman 1998) and often includes variables such as the one-month T-Bill yield, the dividend yield, term spread and credit spread. An alternative approach to estimating a conditional model is to split the data sample on the basis of the public information signal (e.g. for recessions and booms) and estimate separate performance regressions in each period.

Alternative Methodologies

Isolating the causes of future mutual fund performance is clearly a more difficult task than determining the source of good/bad performance in sporting contests (e.g. Basketball, baseball, American football, ice hockey). For sporting contests it is easier to agree on a suitable measure of "performance" and to measure its outturn (e.g. position in the league, achieving the playoffs). Player skill can be measured by the wage bill and the skill of the head coach by whether he/she was a star player. We are interested in variables that may influence future fund performance. Potential causal factors can be classified as follows.

(i) fund characteristics, e.g. size, age, expense ratio, turnover, net inflow of funds, commonality in stock holdings, manager compensation structures, competitive pressures, discretionary versus liquidity induced trading, how "active" is the fund etc.

(ii) manager characteristics/skill, e.g. academic qualifications, age, years with the fund, past performance of the manager, "connectedness" of fund manager with CEOs etc.[10]

(iii) internal governance and strategic factors, e.g. corporate culture, how fund families apportion investment opportunities, mergers and acquisitions etc.

Since the relationship between the future abnormal return $\alpha_{i,t}$ and fund characteristics may vary over time a Fama-MacBeth (1973) cross-section rolling regression is often adopted:

$$\alpha_{i,t} = \theta_t + \delta_t^{'} X_{i,t-k} \tag{4}$$

where X_{t-k} is the m-vector of fund and manager characteristics at time *t-k*. An alternative is to estimate [4] using a suitable estimator for an unbalanced panel[11].

A second method uses a *recursive portfolio approach*. Here, for example, using monthly data we might classify funds into deciles at time *t* based on *any* fund attribute (e.g. past performance or active share) and form (equally weighted or value weighted) decile portfolios[12]. The portfolio holding period, *t+h*, is then established (e.g. h=12 months) and the monthly returns noted, after which rebalancing takes place and new decile portfolios are formed[13]. This gives rise to a sequence of monthly *ex-ante* 'forward looking' (or 'post-sort') returns $R_i^f(t,T)$ - where $t = t+1, t+2, \; ...T$ [14] which are then used to assess future performance.

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[10] Since data on the identity of fund managers over time is somewhat sparse, studies which measure returns to specific fund *managers* are much less prevalent than those which measure returns to the fund itself. This is not a major drawback if a fund's strategy is largely a group decision. However, it is clearly of interest for investors to assess whether performance is due to actions of the "fund as a group" or mainly due to the fund manager. For example, if there is a change in the fund manager this may signal a change in future performance.

[11] Pastor, Stambaugh and Taylor (2014) note that any omitted variables in this equation (e.g. unobserved skill of the fund manager) which are correlated with the included $X_{i,t-k}$ variables (e.g. fund size) implies that OLS estimates of δ are biased. Including fund fixed effects can remove the bias if fund skill is time-invariant but this then implies the need for an instrumental variables approach. In short, estimation of future performance in a panel data approach is not straightforward.

[12] Clearly in principal the weighting schemes can be many and varied. The "smart money" literature weights future returns by "net new inflows as a percentage of AUM", to distinguish the return to "new money inflows" from returns on the whole of the fund's assets (i.e. "new" and "old" money). Some studies (sort funds and) weight funds based on prior alphas, Sharpe ratios or information ratios (Blitz and Huij, 2012). For a cornucopia of possible alternative weighting schemes one only has to look at the academic literature on portfolio theory (e.g. DeMiguel et al (2009) for an overview) and the professional literature on smart beta (e.g. see Arnott et al 2005). The dangers of data snooping are obvious.

[13] When a fund dies sometime over the forward looking horizon, it is usually included in the portfolio until it dies and the portfolio is then rebalanced amongst the remaining 'live' funds, until the next rebalancing period. If we do not implement this procedure then 'look-ahead bias' ensues.

[14] In some studies there is a gap between the rebalancing dates and the measurement of post-sort returns. For example, at each rebalancing date we might track future returns only over horizons from *t+3* to *t+15* rather than from *t* to *t+12* – this

The advantage of the multivariate regression approach is that many candidate independent variables can be included and $\delta_t^{'} = \{\delta_{1t}, \delta_{2t,} ... \quad , \delta_{mt})$ measures the marginal impact of each variable. The drawback is that results are only indicative and do not guarantee an "implementable investment strategy".

For example, in the multivariate regression approach, high past performance may statistically predict high future fund performance, i.e. persistence in performance. But sorting funds (each month) solely on the basis of high past returns may not result in high future performance. To see this, suppose funds which experience high net inflows (of investor cash) have lower future performance, (i.e. diseconomies of scale because managers cannot quickly discover and successfully execute trades in underpriced stocks. But if high return funds are also funds which experience high net inflows then forming a portfolio of funds based on a *single sort* on past returns may not result in high future performance - because any performance persistence may be more than offset by the diseconomies of scale.

In this simple case the solution is obvious. Undertake a prior "double sort" of funds into a "high past return-low cash inflow" portfolio[15] and this might result in high future performance. However, this cannot be guaranteed as other factors which influence future returns (e.g. fund size, turnover, age etc.) might not "wash out" amongst the funds in your double sort. The more funds included in the "potential winner fund portfolio" the more chance these "other factors" may wash out but this cannot be guaranteed.[16] Clearly there are data limitations on how far one can undertake multiple sorts. Also, the R-squared statistics of panel regressions on future performance are often less than 10% so there are a large number of purely random factors that influence future returns which in a (fractile sorted) portfolio of funds may not average out to zero.

The multivariate approach may therefore give some indication of a small number of key characteristics that may be important in deciding on appropriate "sorting rules" for the recursive portfolio approach. But actually implementing the latter approach is the only way to test whether a particular *ex-ante* investment strategy has been successful (on past data).

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allows a test of longer horizon persistence, without confounding the results with short-horizon persistence (e.g., see Teo and Woo, 2001).

[15] The order in which you sort the funds (e.g. first by past return and then by cash inflow or first by cash inflow and then by past returns) may give a different set of funds in say the top decile.

[16] One could carry on and undertake a triple sort on (say) past performance, past fund inflows and fund size but this still relies on "other characteristics", which influence future returns within each of these portfolios of funds, "cancelling out".

Whatever sorting criteria are chosen, within any fractile portfolio funds may be quite heterogeneous (e.g. the top past return fractile may contain funds with quite a large variation in fund size, turnover, styles, etc.) Sorting into finer fractiles (e.g. top 1% of past performers rather than the top 10%), reduces the probability of other factors "cancelling out" and increases the idiosyncratic risk of the portfolio. Thus the smaller the fractile used, the more likely is non-normal idiosyncratic risk - hence bootstrapping techniques may be needed for valid inference.

3. FUND CHARACTERISTICS: PREDICTING FUTURE PERFORMANCE

In this section, we discuss key empirical findings on the predictive ability of mutual fund characteristics in determining future performance. First, we discuss the determinants of fund flows and whether high inflow funds are associated with higher future performance – that is, whether "money is smart". Second, we examine whether the size of the fund and the size of the industry as a whole influence future performance and also how other competitive forces (e.g. fund entry) impact on performance and costs. Next, we examine how alternative measures of "purposeful activity" (e.g. active share, industrial concentration, turnover etc.) affect performance, before finally discussing the importance of incentives on performance.

3.1 Fund Flows

We are interested in the determinants of flows into and out of funds for three main reasons. First, high net inflows increase assets under management (AUM) and hence the fund management company's profits, while high net outflows might trigger strategic changes by the fund (e.g. manager change, change of investment style) in an attempt to improve future performance. Second, cumulative net inflows increase the size of some individual funds and possibly the size of the mutual fund industry as a whole and if there are diseconomies of scale at the fund and industry level, this may reduce future individual and average fund performance – we discuss this further below. Finally, assuming investors are smart and can predict future winners, an increase in net inflows of cash into a fund may signal higher future performance, because the skill of the managers in picking "new" winner stocks outweighs any diseconomies of scale caused by the inflow of new funds.

The determinants of fund flows are usually investigated using a panel data approach. On US data it is found that net new inflows[17] are larger, the higher are past raw returns (rather than past 4F-alphas), turnover, 12b-1 (advertising) fees, and the younger is the fund[18]. The fund flow-

[17] Fund flows are usually measured as $\%Flow_t = [NAV_t - NAV_{t-1}(1+r_t)] / NAV_{t-1}$

[18] Sometimes the size of the fund is found to have a negative impact on flows.

performance link is convex with a disproportionate inflow accruing to the very top prior performing funds (Ippolito, 1989; Gruber, 1996; Chevalier and Ellison, 1997; Massa, 2003; Nanda, Wang and Zheng, 2004; Barber, Odean and Zheng, 2004; Del Guercio and Tkac, 2002; Ivkovic and Weisbenner, 2009; Sirri and Tufano, 1998; Jain and Wu, 2000; Kacperczyk and Seru, 2007)[19].

The *slope* of the flow-performance relationship may also depend on "participation costs" (i.e. expense ratios and load fees, star affiliation and fund family size) - Huang, Wei and Yan (2007). However, future net cash flow is less sensitive to poor past performance (for a variety of alternative performance measures) - see Lynch and Musto (2003), Sirri and Tufano (1998), Chevalier and Ellison (1997), Del Guercio and Tkac (2002). Similar results are found on UK data[20].

New inflows are also influenced by strategic decisions of the fund. For example, Cooper, Gulen and Rau (2005) examine 332 funds which changed their names over the period 1994-2001 to reflect a current 'hot style'. The subsequent extra cash inflow attributable just to the (cosmetic) name change to a "hot style" is a substantial 25% after one year (in excess of flows to matched funds with no name change).

The above studies clearly show that inflows into managed funds respond positively to good past performance, high turnover, high advertising expenditure and lower fees in a rational way - and this is also found to be the case for *index* funds (Elton, Gruber and Busse 2004). As fund flows largely determine management company profits then these determinants of flows are likely to be used by fund management companies in a strategic way. Suppose managers do "manipulate" variables to increase fund inflow and their remuneration, then it is important to determine whether these high-inflow funds yield higher future performance for investors – we discuss this below.

Fund flows and performance persistence

[19] Chevalier and Ellison (1997) note that the convex performance-flow relationship provides an incentive for mangers who are performing worse than the market in the first part of the year to increase the variance of their returns in the second part of the year, since they obtain a very large increase in fund inflows (and hence fees) if they are successful but do not suffer large inflows if they are unsuccessful. This is similar to the Goetzmann et al. (2007) idea of performance manipulation. Evans (2010) notes that some (but not all) of the large impact of past good performance on inflows is due to incubation bias, since incubated funds tend to have high past returns and their *percentage* inflow is also high (because they are relatively small funds).

[20] For the UK Fletcher and Forbes (2002) examine whether cash flow is linked to past performance. Ranking funds recursively into quartiles annually on past year excess returns reveals that the highest performing quartile experiences the largest cash inflow during the year. The worst quartile experience the least cash inflow, but do not suffer an absolute cash outflow, which suggests little penalty for their relatively poor performance. This is corroborated by Keswani and Stolin (2008), who have monthly data separately for inflows and outflows and where past performance is measured using 4F-alpha (estimated over the previous 36 months).

There are so many *ex-ante* sorting rules that have been tested in the literature that it would be surprising if some did not result in positive performance in the future – the possibility of finding false discoveries must be high. Results on the success of *ex-ante* performance vary somewhat depending on whether performance is based on 4F-alpha or a style-adjusted return using a specific benchmark. Generally, results are largely invariant for portfolios based on rebalancing/holding periods of 1 month to 1 year.

It is difficult to generalize but most published *ex-ante* sorting rules in the major journals provide some evidence that funds can be sorted into future "winner portfolios"[21] - and there is much stronger evidence of statistically significant "loser funds". Based on a single sort, future winner portfolios generally have fairly moderate forward looking 4F *net* alphas of 1-2% p.a. which are marginally statistical significant with t-statistics of around 2. When *benchmark adjusted net returns* are used as the performance measure, the top fractile "winner" portfolio tends to have somewhat higher t-statistics than those reported for the 4F alpha performance measure. The question remains as to whether this is exploitable after transactions costs such as load fees, advisory fees and search costs. On the other hand, future loser portfolios have point estimates for net alphas of -1% to -2.5% p.a. and are somewhat more statistically significant (t-stats of -3 to -4).

Any attempt to summarize such disparate studies on different data sets and methodologies is an unenviable task. The solution to this problem is obvious but has escaped the profession - namely a replication study on a common data set resulting in a Cochrane analysis (http://www.cochrane.org) of extant studies - as is regularly done in the medical literature.

In looking for successful sorting strategies there has been much analysis of whether past winner (loser) funds continue to be future winners (losers), that is, "momentum" or "persistence" or alternatively, whether there is mean reversion in performance, that is, past winners (losers) become future losers (winners). For example, Carhart (1997) sorts on past raw returns, Blake and Morey (2000) sort on Morningstar 5-star ratings. Prior (top alpha decile) winner funds tend to mean revert (to zero or negative alphas) while past loser funds (negative alpha deciles) tend improve and retain smaller but still negative forward net alphas.

Bessler et al. (2010) examine whether mean reversion for prior winners and losers is due in part to the size of fund inflows ("external governance") or to a change in fund manager

[21] At the margin, journals probably tend to publish articles which at least demonstrate some successful strategies – "winning strategies" are probably viewed as more interesting than "loser strategies" (Harvey and Liu 2014, 2015).

("internal governance"). They find that the past winner decile (positive alpha funds) experience a smaller fall in their alphas (over the next year) if they either have low inflows or they *retain* their manager. Also, the past loser decile (negative alpha) funds experience a larger rise in their alphas (over the next year) if they either have low inflows or they *change* their manager. This is consistent with high inflows into past winner or past loser funds leading to diseconomies of scale and lower future performance (Berk and Green, 2004). Conversely, retaining prior successful managers in past winner funds and firing bad managers in past loser funds moves the future *change in* performance in a positive direction[22].

Several studies sort funds based on past fund flows on the grounds that investors may be "smart", recognize manager skill and disproportionately allocate new cash inflows to high inflow funds - which subsequently perform well. For example, a portfolio of funds based on prior high past inflows gives a positive 3F-net alpha (Zheng, 1999) but this does not carry over when using the 4F-net alpha (Sapp and Tiwari, 2004). Cooper, Gulen and Rau (2005) find that funds which undergo a cosmetic name-change and attract substantial additional net inflows have lower subsequent raw returns and 3F-alpha performance than matched funds with no-name changes. Keswani and Stolin (2008) on UK data over the period 1992-2000 find that with *monthly* portfolio rebalancing and sorting on past cash inflows, the subsequent net 4F-alpha is negative.

3.2 Fund and Industry Size

Pastor, Stambaugh and Taylor (2014) examine how fund size and industry size influence future performance. Using a panel data approach (1993-2011) they find that a fund's benchmark-adjusted gross return performance[23] deteriorates with fund size and with industry size, with the latter having the strongest effect. Hence there are statistically significant decreasing returns to scale at the fund and particularly at the industry level. However, if fund size and industry size are held constant, then the fund-specific gross (benchmark-adjusted) return[24] increases over time but is lower for older funds. The increase over time is due to more skilled funds entering the industry, while older funds experience decreasing returns to fund size, as the fund matures.

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[22] The Bessler et al (2010) paper is about "*changes* in alpha", conditional on past performance, flows and manager change and is not about discovering "future winner portfolios". Note, however, that even with a three way sort of funds into the "top decile past winner/low inflow/ no manager change portfolio" has a forward looking alpha of 2.16% p.a. which is just significant (at 5% level) while the bottom decile past loser portfolio continues to have statistically significant negative alphas regardless of having a "low/high inflow" or "with/without manager change"

[23] The benchmark index is selected for each fund category by Morningstar.

[24] This is measured by the "fund fixed effect" $R_{i,t} = \alpha_i + \delta_i X_{i,t-1} + \varepsilon_{i,t}$ (i.e. constant "intercept", α_i for each fund over time, in the panel regression).

They also find that the *average industry* gross (benchmark-adjusted) return remains constant over time. We can reconcile increasing fund-specific (gross) alphas over time with average industry alphas that remain constant over time. If new (small) funds entering the industry have higher skill sets, their (relatively small) trades have less adverse price impact and this will tend to increase *average* performance over time. But average gross performance is also adversely affected by the increasing size of the *industry* which reduces the potential for profitable trades (e.g. because anomalies are quickly arbitraged away or there are adverse price impact effects, due to industry size). These two effects cancel each other out so that average *industry* performance remains constant.

3.3 Competitive Forces

Gil-Bazo and Ruiz-Verdu (2009) use the degree of overlap in stock holdings between incumbent funds and new entrants as a measure of "competitive pressure". Using the Fama-McBeth approach, they find that after 1998 (when the number of funds increased rapidly), incumbent funds which experience an increase in competitive pressure subsequently reduce their management fees but increase their 12b-1 (advertising) fees, so the net impact of increased competition on *total fees* charged (i.e. price competition) is small. But an increase in competitive pressure on incumbents leads to reduced fund inflows over the next 2 years (particularly for the previously high quintile past performers) and an increase in attrition rates (over the next 5 years) for prior poor performing funds. This indicates that competitive forces have an impact on management company income and the overall effect of increased competition is to reduce *incumbent funds*' 4F net-alphas.

3.4 Activity and Diversity as Proxies for Fund Skill

To measure the "purposeful activity" of a fund, there are many potential avenues. For example, a larger tracking error[25] is sometimes used as a proxy for higher skill and is therefore assumed to result in higher future performance. Similarly, an increase in "active share" (AS) namely, the fraction of a fund's portfolio that differs from the index[26], is taken to be indicative of higher future performance. The industrial concentration of a fund's stockholdings is another measure of

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[25] Tracking error is measured as the standard deviation of the fund return minus its benchmark return

[26] AS measures the (absolute) deviation of a fund's (percentage) stock *holdings* from the average holdings in the fund's benchmark return (e.g. S&P500). The Active Share index is $AS_{i,t} = (1/2)\sum_{k=1}^{N} \left| w_{k,t} - w_{bench,k,t} \right|$ where $w_{k,t}$ is the (value) weight of fund-i's holdings of stock-k in period t and $w_{bench,k,t}$ = (value) weight of stock-k in the fund's *benchmark index*. AS=100% implies no overlap of the fund's holdings with the constituents of the index (i.e. "active"), while AS=0% implies the fund's holdings are held in the same proportions as stocks in the index ("closet indexer").

"activity" – that is, concentrated fund holdings of stocks in a particular industrial sector, signals higher future performance. Skill depends on private information of the manager (or fund). Hence, funds whose changes in stock holdings are *not* strongly related to changes in analysts' stock recommendations, are deemed to be "highly selective" and should be rewarded with higher future performance[27] (Kacperczyk and Seru, 2007). These alternative "activity measures" try to calibrate how much a specific fund activity "differs from the crowd".

Active share

As an example of applying the two methodological approaches, we present some results from a highly cited article by Cremers and Petajisto (2009). Based on a multivariate panel data regression (and in common with many other studies) they find that over the period 1990-2003, next year's benchmark adjusted return[28] depends positively on a fund's lagged AS, last year's benchmark adjusted return and the greater the number of stocks held[29]. In addition, future performance depends negatively on lagged fund size[30], fund age and recent net inflows of cash – the latter suggests that "money may not be "smart". From the multivariate regression results, a strong candidate for a recursive portfolio single sort is a fund's AS.

Over 1990-2003, Cremers and Petajisto (2009) perform a *double sort* into (5x5) quintile portfolios based on active share and past (benchmark-adjusted gross) returns. The top "high AS-high past return" portfolio has an impressive *net (benchmark-adjusted) return* 4F-alpha of 3.5% p.a. (t=3.29) but 17 of the remaining 24 portfolios have statistically significant negative net (benchmark-adjusted) return alphas.

The multivariate analysis also shows that *small* funds provide higher future 4F-*net* alphas than large funds. A 5x5 sort on fund size and AS gives a 4F net-alpha $\alpha_{4F}^{f,net}$ = 1.71% (t=1.97) for the "small size-high AS" quintile. Future performance after a three-way sort is even stronger. Over the 1990-2003 period, sorting funds first into below-median-size and then into the highest AS quintile and finally into the highest past return quintile gives a remarkable net-benchmark adjusted return of $(r_p^{net} - r_b)$ = 6.49% p.a. (t=4.40) with a 4F alpha , $\alpha_{4F}^{f,net}$ = 4.84% p.a. (t=4.04).

[27] "Reliance on public information" (RPI) of a fund is measured by the R-squared of a fund's change in portfolio stock holdings on lagged values of the change in the consensus analysts forecast for specific stocks in the fund's portfolio. The lower is RPI the more active the fund and the higher the fund's future performance (Kacperczyk and Seru, 2007).

[28] They do not use a self-declared benchmark. They compute the AS of a fund for several alternative benchmark indices and choose that benchmark index which has the lowest AS.

[29] They also find that future performance is not significantly related to turnover, manager tenure or tracking error.

[30] See for example, Kacperczyk and Seru (2007), Chen et al. (2004), Yan et al. (2008), Bris (2007), Pollet and Wilson (2008), who all find some evidence of a negative effect of fund size on fund performance, although Ferreira et al. (2013) and Reuter and Zitzewitz (2013) find no such effect. The negative size effect on future fund performance is also stronger for funds which hold less liquid stocks (Yan et al., 2008).

In a later paper using AS, Cremers and Pareek (2014) extend the data period to 1995-2013, use self-declared benchmarks, rebalance annually (not monthly) and measure alpha with respect to a 5F model (which includes a liquidity factor) using net benchmark-adjusted returns, $(r_p^{net} - r_b)$ [31]. A single sort into AS quintiles over the extended data period 1995-2013 gives no statistically significant positive outperformance to investors (either for net benchmark-adjusted returns or their 5F net alphas). A double sort into 5x5 (equally weighted) quintiles based on "fund duration"[32] and AS, gives a 5F net-alpha of 2.30% p.a. (t=3.14) for the "high AS-long duration" quintile portfolio (that is, funds which hold stocks that are different from their self-designated benchmark and are also traded infrequently). For the other sorted portfolios, 16 out of 25 have (5F) net alphas which are negative and statistically significant and 8 alphas which are not statistically different from zero. However when the "high AS-long duration" quintile portfolio net benchmark-adjusted returns are subject to a 7F model[33] the net alpha drops to a statistically insignificant, 0.59% p.a. (t=0.83).

To some, the moral of the story is that if you search long and hard enough you will discover a "winner strategy"[34]. To others, who correctly note the high level of transparency of most academic studies, this indicates genuine *ex-ante* skill for the chosen subset of (sorted) funds and is not a false discovery. As far as the future success of any strategy is concerned, that will in part depend on how many investors try to exploit the anomaly once it has been revealed. If many investors use the strategy in the future, any mispricing on which it is based may be arbitraged away and increased net inflows may reduce future performance. Then active investors have to find and switch to an alternative potentially successful strategy - as yet undiscovered by other market participants.

In qualitative terms the above study broadly represents results from many *ex-ante* strategies for picking potential winner fund portfolios (see below). Usually, finding positive forward looking *gross* alpha portfolios is possible (for the "extreme" fractile portfolio) but *net* return alpha performance is extremely difficult to detect and often only borders on statistical significance - even after quite extensive search procedures, at least a double sort on fund

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[31] They also report results for Daniel, Grinblat, Titman and Wermers (1997) DGTW benchmark adjusted returns and also examine performance of "institutional portfolios" (bank's trust departments, pension, insurance, hedge funds and endowment funds and funds managed by investment advisors).

[32] Fund duration is a weighted measure of buys and sells by a fund, with the weights being the length of time the stock has been held over the past 5 years. " Low duration" indicates stocks are held for a relatively long period of time – i.e. the fund trades infrequently and the fund (manager) is a "patient investor".

[33] The additional factors added to the 5F model are the "betting against beta" (Frazzini and Pedersen, 2014) and the "quality minus junk" factors (Asness et al., 2015). Only the market factor and the liquidity factor are statistically insignificant.

[34] For example, the cynic might assert that a quintile sort based on the maximum "Scrabble" score of the fund's name may provide *ex-ante* "winner funds". Indeed, Frazzini et al (2015) record that from all actively managed US domestic

characteristics and after alternative benchmarks and statistical methods have been applied. In contrast, negative *net* return alpha performance is pervasive and persists.

Industrial Concentration

Active share is one measure of "deviating from the crowd" in order to obtain a successful trading rule (Cremers and Petajisto 2009). Similarly, Kacperczyk et al (2005) find evidence that the degree of industrial concentration (ICI), relative to the market index, (i.e. the deviation of fund holdings from passive industry weights), can be used to predict future fund returns.

Turnover

Another measure of "activity" is fund turnover. Higher turnover implies higher (dollar) trading costs which tends to reduce fund returns - but this may be offset by more substantial profitable trades by skilled managers. For 1979-2011, Pastor, Stambaugh and Taylor (2015) find that next month's *gross* returns (over their Morningstar designated benchmarks) are positively related to turnover and this relationship is strongest for small funds and funds with high expense ratios.

In order to help understand why high turnover funds have high returns, Pastor, Stambaugh and Taylor (2015) look at the determinants of turnover. They find that higher average industry turnover is correlated with a higher potential for exploitable stock market anomalies. On average, funds trade more when positive sentiment in the stock market is high, when the cross-sectional volatility in stock prices is high and when liquidity is low - consistent with skilled funds capitalizing on more profitable anomalies by trading more in these periods. Using panel data, they find that future fund performance is positively related to fund turnover, average industry turnover and positive sentiment in the stock market. In addition, *industry* size has a negative impact on future performance – indicating decreasing returns to "industry expansion".

However, sorting funds into tercile portfolios based on past turnover and rebalancing monthly does not give a positive statistically significant future average *gross* (benchmark-adjusted) return[35] (Gross R = 0.0626% p.m. , t=1.80) - unless the high turnover portfolio is formed immediately following high positive sentiment months (Gross R = 0.1329% p.m., t=2.25). However, all future *net* benchmark-adjusted returns *to investors* are never statistically significant for any tercile based on a double sort on turnover and sentiment[36]. Once again, it is not possible to find an *ex-ante* (double) sorting strategy that is beneficial to investors.

mutual funds (1980-2009) those sorted with "K" as the first letter of the fund's name have a lower average return than "Q-funds" by 2.3% p.a. (t=1.64).

[35] They use the Morningstar benchmark index to adjust the gross fund return

[36] Cremers and Pareek (2014) find that funds that are both low turnover (i.e. "patient") and have high AS, perform relatively well, whereas Pástor, Stambaugh and Taylor (2015) find evidence that high turnover funds (after high positive

Unoberved Actions

Kacperczyk, Sialm and Zheng (2008) investigate whether a fund's actions *between* portfolio disclosure dates provides incremental information which could be used by investors to pick winners. They measure the "unobserved actions" of funds by the *return-gap* – the difference between the observed quarterly net return and the quarterly buy and hold return (using previously reported portfolio weights). The return gap measures any benefits of interim trades (less any transactions costs), over each quarter. However, sorting funds on the past return-gap gives no future outperformance unless we also use a 'predictive filter'[37] which results in $\alpha_{4F}^{f,net}$ = 2.52% p.a. (t=1.98). The latter is due in part to higher "hot" IPO allocations being allocated to high return-gap funds (Cooper, Gulen and Rau, 2005), which might also be funds affiliated to the lead underwriter (i.e. the nepotism hypothesis, Ritter and Zhang, 2007). These IPOs are the source of the "success" of the "unobserved actions" of these funds.

Reliance on Public Information, (RPI)

The idea that skill resides with specific activities of funds is taken up by Kacperczyk and Seru (2007) who develop a theoretical model whereby skilled funds rely less on publicly available information (because it is already compounded in prices) and more on private signals. The "reliance on public information" (RPI) of a fund is measured by the R-squared of a fund's change in portfolio stock holdings on lagged values of the change in the consensus analysts forecast for specific stocks in the fund's portfolio. Sorting funds on RPI and rebalancing monthly gives a statistically significant $\alpha_{4F}^{f,net}$ of 2.16% p.a. for the long-short portfolio (top minus bottom 30% of ranked funds). However, it is not clear how much of this is due to holding the high-skill ranked funds (i.e. low RPI funds) versus shorting the low-skill funds, and as mutual funds cannot be short sold, this long-short strategy is not exploitable by investors.

Commonality

Cohen, Coval and Pastor (2005) provide an alternative ranking metric for potential fund skill based on 'commonality', that is, how closely a particular fund's stock holdings currently mimic the

sentiment months) perform relatively well. These two results are difficult to reconcile, although both studies find that positive investor (i.e. net benchmark-adjusted) returns are difficult to detect.

[37] The 'predictive filter' used is similar in spirit to that of Mamaysky, Spiegel and Zhang (2008) and is to only include funds where the *sign* of the average excess return (over the market return) equals the *sign* of the return gap.

stock holdings of funds which have recently performed well (based on their past alphas)[38]. For example, over April 1982 - September 2002 based on a (5x5) double sort they find the "highest-alpha, highest-commonality" ranked portfolio has 4F-gross alpha of $\alpha_{4F}^{f,g}$ = 4.61% p.a. and the bottom ranked portfolio has $\alpha_{4F}^{f,g} =$ -3.79% p.a. with the long-short portfolio yielding 8.4% p.a.[39] (significant at the 1% significance level).

Incentives

Massa and Patgiri (2009) define "high incentive funds" as those with a linear compensation structure and "low incentive funds" as those where the percentage advisory fee declines as total assets increase. Using a (5x5) double sort (with annual rebalancing) based on past 4F-alpha and "managerial incentives", Massa and Patgiri find that last years "high return-high incentive" funds have a substantial $\alpha_{4F}^{f,net}$ = 4.8% p.a. (t=2.36) over the period 1996 – 2003. Persistence in past "high incentive-winner funds" is found to be due to an active strategy, since "unobserved actions" rather than buy-and-hold returns are the main contributor to the winner funds' performance.

Discretionary and liquidity trades

Alexander, Cicci and Gibson (2007) classify "active skill" by a (5x5) double sort based on net flows and the dollar value of trades. 'Valuation motivated trades' are defined as large dollar-buys (sells) which take place when there are heavy net outflows (inflows) while 'liquidity motivated trades' are funds where small dollar buys (sales) are accompanied by large inflows (outflows). Using 324 US equity funds (January 1997-December 1999) they find some evidence of skill for 'valuation motivated trades'.

Utility

The above studies often use equally weighted portfolios. In contrast, Avramov and Wermers (2006) choose *optimal* portfolio weights at each monthly rebalancing date, in order to maximize

[38] Essentially fund-i's 'skill' (= $sk_{i,t}$) is a weighted average of other funds' alphas, with the weights depending on the covariances between fund-i's portfolio weights and the current weights of the other managers. If fund-i holds only stocks that are held by no other manager then $sk_{i,t}$ collapses to α_i, otherwise $sk_{i,t}$ is high if it has portfolio weights which are similar to portfolio weights of other funds with high alphas. The analogy they use is that after observing a group of basketball players you note that the average score is 8/10 for the two-handers, but only 4/10 for the one-handers. Then if two players, one one-hander and one two-hander are observed, each currently with a 4/5 score, then you would bet that the two-hander is more likely to have a higher score out of 10 - the track records of the other two-handers are better than the one-handers, so you assume the current two-hander has a better technique and the one-hander is more likely to have been lucky with his first 5 shots.

[39] Separate t-statistics for the "top" and "bottom" portfolios are not given, so we cannot infer if the strategy gives statistically significant abnormal returns solely to the 'winner' portfolio, which would remove the problem of short-selling mutual funds. Also, the figures reported above are the largest found for the various sorts, across a variety of models.

next periods quadratic utility (which depends on mean portfolio return and variance)[40]. The forecast of next period's returns depend on predictability in the factors which themselves are driven by macroeconomic variables such as the dividend yield, default and term spreads and the interest rate[41]. This approach results in a forward looking portfolio which yields a $\alpha_{4F}^{f,net}$ that is statistically significant and very large, ranging between 9-12% p.a. Clearly, the *ex-post* performance of this 'optimal portfolio strategy' is substantial but it appears that investors would have to mimic holding up to 1,300 funds and rebalance every month – an issue that needs further investigation particularly with respect to transactions costs (e.g. load and advisory fees).

This concludes our discussion of the predictive power of *fund* characteristics on future fund performance. Other branches of the mutual fund performance literature deal with the impact on performance and risk taking of first, *manager* behavioural biases and *manager* characteristics/attributes and second, fund management *company* governance, strategies and organisational structure. We will see that a discussion of the impact of managerial behavior and organisational structure on fund performance is linked to how performance is influenced by fund characteristics such as size, fund flows, active share etc. in the above discussion.

4. BEHAVIOURAL BIASES, MANAGEMENT EFFECTS AND FUND PERFORMANCE

Behavioural finance recognises that investor psychological biases often inhibit the workings of rational models. First, although models based on rational agent behaviour are theoretically defensible, it is questionable, indeed often strains credulity, that they are foremost in the minds of investment practitioners. Second, human emotions such as fear and greed as well as the adoption of heuristic processes in investment decision making give rise to psychological or cognitive biases that lead to deviations in investor behaviour from those predicted by rational models. Manager behavioural patterns include excessive trading, overconfidence, a disposition effect, herding, window dressing, risk taking and home bias while behavior is also impacted by issues such as career concerns (employment risk), fund ownership and performance related incentive fees. In this section we review the literature on the impact of manager behavioural effects and manager characteristics on fund performance and risk taking.

[40] Funds include actively managed funds, index funds, sector funds and exchange traded funds (ETFs). They allow investors to hold (positive) weights in these 1,301 (no-load domestic equity) mutual funds over the period December 1979 to November 2002. In this mean-variance framework, there are no hedging demands - for the importance of the latter see, for example, Ait-Sahalia and Brandt (2001), Campbell et al (2003), Viceira (2001), Cuthbertson and Nitzsche (2004).

Employment Risk

We introduce our discussion by examining employment risk as this is a key motivation behind manager behaviour. Employment risk refers to managers' career concerns, in particular the fear of being fired primarily as result of poor performance. For example, herding behaviour is driven by a fear of conspicuous poor performance relative to peers. Similarly, window dressing behaviour is an *ex-post* attempt to disguise poor performance relative to peers. Fund manager career concerns around employment risk are well founded. Khorana (1996) finds that manager dismissal is preceded by poor performance for up to two years prior to dismissal.

In a comprehensive study, Hu, Kale, Pagani and Subramanian (2011) find a U-shaped relationship between manager risk choices (relative to their peers) and their prior relative performance - both top and bottom performing managers exhibit 40% increased risk in the second half of the year (relative to the minimum risk level) [42]. Top-performing managers face lower employment risk in the future and hence are more likely to increase relative risk while under-performing managers face greater employment risk and are more likely to increase risk in a bid to 'catch-up' with their peers.

As discussed in previous sections, there is strong empirical evidence that good relative performance leads to strong fund inflows but poor relative performance does not lead to commensurate outflows. Hu et al. (2011) contend that any factor that increases (decreases) the convexity of the fund flow-performance relation also increases (decreases) the convexity of the U-shaped relative risk-prior performance relation. This is because the fund flow – past performance convexity means, for example, that a fund with poor prior performance is incentivized to increase risk in the knowledge that the impact on fund flows is non-linear. For example, higher expense ratios reduce the convexity of the fund flow-performance relation and funds with higher expense ratios are found to have less convex U-shaped relations between relative risk and prior performance.

Overall, therefore, investors should be wary of investing with recent poor performing managers not only because of the obvious indication that they may be less informed but also because of their behavioural tendency to increase risk. Recent high performing managers also tend to increase risk but it's not clear whether this behaviour is informed. It would be useful to

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[41] The model of fund returns is the 4F conditional alpha-beta model, where the 4-factors each depend on the lagged macroeconomic predictor variables z_{t-1} and the latter are themselves forecast using a VAR model.

[42] Relative performance in each half-year is the return, before costs and fees, in excess of the fund benchmark during the half-year and relative risk is the standard deviation of the fund's relative performance.

examine the precise nature of the increase in risk as high performing managers typically enjoy net inflows which other studies have found reduce risk, at least in the short run, as the inflows are temporarily placed in lower risk cash-type investments (Edelen, 1999).

Employment risk is related to two further behavioural effects. First, window dressing, that is, divesting poor performing positions and 'decorating' the portfolio with more favourable looking stocks prior to periodic reviews and holdings disclosures. Second, herding, that is, buying the same stocks as peer group managers in a 'share the blame' effect.

Window Dressing

The SEC requires mutual funds to disclose holdings information within 60 days after a quarter-end. This may incline fund managers to window dress the portfolio in an attempt to disguise otherwise conspicuous poor past investment decisions. Window dressing behavior raises a number of questions. In particular, whether investors are misled by it.

Wang (2012) finds that a significant proportion of funds engage in window dressing. Wang compares the momentum loading on a fund's actual returns with the momentum loading on a simulated portfolio based on the fund's subsequent disclosed holdings. If a manager window dresses his portfolio before disclosure, we expect a higher momentum loading on the simulated portfolio. Using the false discovery procedure of Barras, Scaillet and Wermers (2009), Wang (2012) finds that 9.4% of the almost 54,000 transactions in the sample are based on window dressing. The paper shows that funds with past poor performance are more likely to window dress, because of increased employment risk. In addition, Wang (2012) shows that window dressed funds enjoy higher subsequent cash inflows - which suggests that investors are misled by it.

Herding

Herding is motivated by fund managers wishing to avoid poor performance relative to their peers so they "go with the crowd". Herding has implications both for stock prices and fund returns as correlated trading may generate predictable patterns (Lakonishok, Shleifer and Vishny, 1992). Key questions are whether herding is pervasive (Hong, Kubic and Stein, 2005) and if so, what is its impact on fund performance (Jiang and Verardo, 2013; Koch, 2014; Wermers,1999).

There are different definitions of herding behavior. Hong, Kubic and Stein (2005) consider herding in terms of the sensitivity of the trades of any given fund manager to the trades of other managers. Specifically, they find that a given manager's stock weight increases by 0.13% when other managers from different fund families in the same city increase their purchases of the same stock by 1%. Hong et al. establish that the source of the herding is by word-of-mouth, rather than by local TV, newspapers etc. Herding is evident even when the fund manager and the stocks traded are not geographically proximate, so this effect is distinct from home bias or local preference.

A key area of interest is the link between herding behavior and subsequent fund performance. Jiang and Verardo (2013) measure herding by the correlation between a given fund's trades and those of other investors. They find that the top decile portfolio of fund-herders, underperform the non-herders by a 4F-alpha of up to 2.52% p.a. In addition, the authors report persistence in the herding/non-herding performance differential over horizons of six, nine and twelve months. The paper controls for the component of the correlation between fund trades and peer trades that is attributable to mutual funds' momentum investment strategies thus disentangling herding from momentum effects.

Koch (2014) develops an alternative fund level measure of herding based on contemporaneously correlated trading, as well as leads and lags ("followers"). Based on a sample of 2,700 funds between 1989 and 2009, Koch finds that only leading funds are found to outperform over several subsequent quarters.

Herding may be influenced by team behavior. Group shift theory (Kerr, 1992) suggests that team opinion gravitates towards the opinion of the most extreme team member. Conversely, the "diversification of opinion hypothesis" (Sharpe, 1981) suggests that team opinion gravitates to the average opinion of team members so that extreme opinions average out and teams make less extreme decisions than individuals. Bar et al. (2011) put these competing hypotheses to the test on a sample of US equity funds between 1996 and 2003. Specifically, they measure the "extremity" of a fund's investment style as the deviation of its 4F loadings from the average factor loadings of matched funds. They find that the factor loading of single-managed funds deviate more from average factor loadings than those of team managed funds. Consequently, teams achieve less extreme performance outcomes than single managers.

Overall, there is a reasonably strong consensus that herding of various types takes place and that herders and followers subsequently under-perform. It would also be helpful to have information on the characteristics of managers most prone to herding and whether, for example, it is related to the employment risk associated with inexperience and young age, investment style or degree of specialization. This is an area for further research.

The evidence on herding can be linked to our earlier discussion on "diversity" as a proxy for fund skill. In section 3, diversity is measured in a variety of ways including a large tracking error, active share (the fraction of a fund's portfolio that differs from the index), industrial concentration (deviation of fund holdings from industry weights) and reliance on public information (RPI). While herding funds are found to underperform in the future, funds sorted on the above measures of 'deviating from the crowd' are found to outperform, (Cremers and Petajisto, 2009; Kacperczyk et al. 2005, Kacperczyk and Seru, 2007).

Familiarity and Home Bias

Familiarity creates another psychological bias that may cause irrational investment decisions. 'Home bias' is the tendency to disproportionately invest in companies that are head-quartered in an investor's home country, home state or companies located geographically nearby and can result in an under-diversified portfolio. However, home bias may be rational if it arises due to an information advantage.

In a study of global equity fund holdings data in 1999 and 2000, Chan, Covrig, and Ng (2005) find a prevalence of home bias in all of the 48 sample countries studied. Explanations for home bias towards domestic equities include the avoidance of exchange rate risk, variation in regulation, taxation, accounting standards, corporate governance, transaction costs and information asymmetries.

Massa and Simonov (2006) show that investors prefer stocks located nearby because geographic proximity offers familiarity and a lower cost of acquiring information. In an alternative approach, Ke, Ng and Wang (2010) study the US equity holdings of non-US-domiciled ("foreign") mutual funds and find that these funds exhibit a strong preference for US firms with a local presence - a greater proportion of foreign fund managers invest in US firms that have local presence than in those that have no presence. These fund holdings with local presence, however, perform no better than a *passive portfolio* of all US stocks with local presence - suggesting that the local presence of US firms does not provide significant information advantages to local fund managers. Ke et al. also report that investors tend to invest in foreign stocks that are highly correlated with their local market, leading to reduced diversification.

Home bias may represent "informed trading if manages have information about companies at home that gives them an advantage. Using a US sample of 4.7 million quarterly fund holding observations between 1996 and 2009, Pool, Stoffman and Yonker (2012) investigate whether managers overweight companies from their home states and whether these stock selections reflect information based trading. The study finds that the average fund over-weights stocks from its managers' home states (some funds have more than one manager) by 1.34% compared to other funds in the same (Morningstar) category. The expected state weight in the absence of any home bias is 7.12%, implying that the average fund over-weights its managers' home states by 134/712=18.8%. Pool et al. (2012) reveal that greater home bias results in higher fund idiosyncratic volatility as geographically proximate stocks exhibit some co-movement. Home-state stock holdings do not outperform the rest of the fund's holdings suggesting that the home bias is motivated by familiarity rather than informed trading.

Linking home bias to fund and manager characteristics, Pool et al. (2012) document that early career managers exhibit stronger home bias than older managers. They also show that new managers build up their holdings in home-state stocks within a few quarters after their arrival.

Overall, the empirical evidence points to the prevalence of home bias among fund managers, which appears to be an irrational investment strategy involving higher idiosyncratic risk and "home stocks" which do not outperform. In contrast, home bias may arise because "familiar stocks" involve lower search costs and hence rational cost saving benefits.

We continue by examining some further behavioural biases that affect manager performance and risk taking, namely, the disposition effect, manager overconfidence and performance-related incentive fees.

The Disposition Effect

From prospect theory, the disposition effect is the tendency of investors to hold onto losing positions too long and take profits too soon. Riding losses is thought to be driven by a desire to avoid regret and selling winners is driven by a perceived sense of "success". These widespread behavioral biases have been documented in the actions of individuals, corporations and governments (Statman and Caldwell, 1987). The disposition effect has obvious negative implications for investor performance. First, riding losses too long and realizing gains too soon reduces gross returns. A second reason relates to the tax code in jurisdictions such as the US Selling winners incurs a capital gains tax but selling losers creates an opportunity to reduce this tax bill. Hence, riding losses inhibits these tax savings.

The literature on the disposition effect among mutual fund managers is small. However, Jin and Scherbina (2011) investigate the actions of new managers, comparing their trades against the concurrent trades of a matched sample of continuing managers who hold the same stocks (matched on fund performance, fund flows, investment objective and fund size). The authors find that a significantly higher fraction of losing stocks are sold by new managers than by continuing managers as the new managers are less emotionally attached to these positions - supporting a disposition effect.

Following from the well-documented positive relationship between fund net inflows and past performance, Wermers (2003) examines the reaction of investors to fund performance and the resulting behaviour of managers following net inflows. He finds that winning managers use cash inflows to implement momentum strategies more strongly than losing managers. The latter are reluctant to sell their low return stocks - consistent with a disposition effect - and momentum works against them as they hold on to losers that continue to be losers. Momentum trading provides some protection against the disposition effect - as (algorithmic) momentum trades involve selling losers, the manager is less likely to ride a loss too long

It would be interesting to know whether riding losses too long is compounded by home bias, i.e. a particular reluctance to sell 'home' stocks or stocks the manager has had success with in the past. It would also be useful to know whether the strength of the disposition is affected by the personal stake the manager has in the fund, either through direct ownership of fund units or through performance related remuneration.

Overconfidence

Above, we discussed fund managers' reaction to past performance and their subsequent behaviour around risk taking, particularly in the context of employment risk and career concerns. A further dimension to this discussion is the question of self-attribution. In particular, biased self-attribution leads managers to falsely attribute good past performance to their own skill rather than to luck, whilst also attributing bad past performance to bad luck. This can lead managers to an overestimation of their own trading skills where they become overconfident following good performance but not less confident following bad performance (Gervais and Odean, 2001).

Puetz and Ruenzi (2011) find that overconfident investors subsequently trade too much based on their false beliefs around their abilities. Among funds in the top quintile of performers, turnover depends positively on past performance. It is possible that increased trading is rational if informed managers learn about their abilities in a Bayesian context. If this is the case, it should result in better future performance. However, Puetz and Ruenzi find that within the top decile of funds sorted on Carhart 4F-alpha, low turnover funds (below median) outperform high turnover funds (above median) by up to 1.9% p.a.

Overconfidence raises several questions for future research. Does overconfidence explain the positive relationship between past performance and subsequent risk? Does attributing bad past performance to chance cause mangers to ride losses too long? Are managers more likely to be overconfident in relation to investments in home stocks where the comfort of familiarity causes an under-estimation of risk?

Ownership and Incentive Fees

In the US, almost half of all mutual fund managers have personal ownership stakes in the funds they manage, (Khorana, Servaes and Wedge, 2007). This may alter manager behavior and fund performance. Khorana et al. find that while ownership levels are small (typically less than 5%), future risk-adjusted performance improves by around 3 basis points for every one basis point increase in ownership.

Similar to ownership, performance-related incentive fees may also affect manager behavior. The incentive fee is typically a percentage applied to the difference between the fund's return and its benchmark. Incentive fees do not imply ownership in the fund but do give the manager "skin in the game". There is strong evidence that incentive fees alter manager behaviour (Carpenter, 2000). Elton, Gruber and Blake (2003) demonstrate that effective fee rates are convex over lower ranges of performance (and only become concave when the fund is performing very well). This incentivises fund managers to take on more risk and Elton et al. show that incentive-fee funds incur greater risk by deviating significantly more from their stated benchmarks (than a matched sample of non-incentive-fee funds) and they also have significantly higher market betas.

Similarly, performance related compensation schemes for managers, which pay out in times of strong relative performance, incentivise risk taking in the form of deviating from the pack and hence reduce herding. Examining the US market, Dass et al. (2008) find this is particularly the case around the peak of a bubble - where a 1% increase in incentives reduce the portfolio weight in bubble stocks by almost 3%.

The incentive provided by performance-related remuneration to increase risk is further compounded by the convex fund flow-performance relation. If higher risk pays off in terms of better performance then the fund enjoys a net inflow. If not, the fund suffers a relatively small outflow. Fund manager risk taking behaviour arising from such incentives strongly underpin the need for both employers and investors to evaluate and reward managers on a risk-adjusted basis.

In Section 3, we discussed the role of *fund* characteristics in explaining the cross-section of fund performance. Improved data availability has also enabled an assessment of the role of m*anager* characteristics in performance. If the ability to achieve abnormal performance exists, it is not obvious whether it resides in the manager or in the fund organization.

Manager characteristics such as age, tenure, education, gender etc. all potentially matter in manager performance. For example, university attended may be related to the establishment of alumni networks either between fund managers or between managers and CEOs and this in turn may facilitate a flow of relevant information. Behaviours such as risk taking may be linked to age or gender. Such information is now easily obtained from fund prospectuses and so if relevant to performance, provides low cost information to investors in selecting managers.

Manager Characteristics

With a sample of 492 managers between 1988-1994, Chevalier and Ellison (1999) examine the cross-sectional relationship between manager age, the average student SAT score of the manager's undergraduate institution, whether or not the manager has an MBA degree and length of manager tenure. MBA holders outperform non-MBA managers by 63 basis points p.a. but this is explained by the formers' higher holding of systematic risk. A manager who is 12 years older than the mean under-performs the mean manager by 1% p.a. This is largely, but not entirely, explained by fund fees and also by greater survivorship bias among younger managers.

Chevalier and Ellison find a robust positive relationship between performance and managers from undergraduate institutions with higher average student SAT scores. This result could be due to such managers having greater innate abilities or enjoying the benefits of a better education. Alternatively, the high SAT score institution may be picking up benefits associated with a network of connections to other members of the financial community. Finally, the paper finds no significant effect on performance of manager tenure, a result consistent with more recent studies (Costa, Jakob and Porter, 2006).

In a small literature, Switzer and Huang (2007) generally confirm the findings of Chevalier and Ellison, where MBAs do not perform better than their non-MBA counterparts. There is some evidence that managers with the CFA designation outperform, though these findings are model specific and are not robust to fund characteristics including risk, expenses and turnover. However, CFAs do tend to engage in higher turnover. There are no gender-specific performance results, though women exhibit higher systematic risk. Longer tenure is associated with higher expense ratios, but not better performance.

Connected Stocks

Cohen, Frazzini and Malloy (2008) suggest that there is superior information flow in previously established social networks between fund managers and three senior officers of firms (i.e. CEO, CFO, Chairman). They classify stocks held by mutual funds into "connected stocks" based on educational background. For example, the strongest measure of "connectedness" is when a fund manager and at least one of the firm's senior officers attended the same university, overlapped in years attended and did the same degree. Using quarterly recursive rebalancing (1990-2006), the returns on connected stocks earn a significant risk-adjusted return between 2% and 8.7% p.a. (depending on the precise definition of "connectedness"), whereas the unconnected stocks do not earn positive abnormal returns.

The positive returns on connected stocks occur around corporate news announcements - but managers do not sell ahead of bad news announcements. These effects exist across different fund styles, local and distant locations of funds and across ivy league versus non-ivy league universities. This study does not address the overall performance of the fund – which also depends on the performance of the "non-connected" assets.

Summary

Overall, the empirical evidence strongly points to mutual fund managers exhibiting a number of behavioural biases. The literature indicates that both herding and window dressing occur. Managers also display home bias and overconfidence leading to increases risk taking and turnover. There is also evidence that managers display a disposition effect. There is some evidence that manager ownership in a fund and performance-related incentive fees cause managers to increase risk but also to achieve slightly higher risk-adjusted performance. Risk taking in response to past performance is convex and even U-shaped, i.e. is higher among both past good and bad performers but lower among mid-ranked managers. Not surprisingly, manager characteristics as well fund characteristics also explain the cross-section of fund returns where the quality of the undergraduate institution attended by the manager has some positive impact while there may also be an inverse performance–manager age relation. Neither MBA nor CFA qualifications are robust predictors of performance.

In our review of fund characteristics and behavioural biases on fund performance, we find there is little attempt to examine whether performance attributed to such characteristics or ‘irrational’ behaviour might be explained by rational asset pricing. For example, the evidence that younger managers outperform older managers may arise because of a higher required return by investors when investing with younger inexperienced (riskier) managers. Also, the literature suggests that managers who deviate from the crowd are found to outperform but is this related to their higher idiosyncratic risk - which some asset pricing studies have found may be positively priced? Herding has implications for both *individual* stock liquidity (where stocks herded into become more liquid and *vice-versa*) and *market wide* liquidity. However, in the asset pricing literature, these liquidity effects command a return premium (Korajczyk and Sadka, 2008; Foran et al. 2014a, 2014b, 2015).

In the vast bulk of the fund performance literature we review, the unit of analysis is the fund rather than the manager. However, a single time series of fund returns are generally attributable to multiple managers over time whose behavioural biases and characteristics may be quite diverse. This complicates inferences based on fund returns.

5. MUTUAL FUND GOVERNANCE, ORGANISATIONAL STRUCTURE AND STRATEGIES

We now shift our attention from manager behavioural biases and characteristics to the impact on fund performance of *mutual fund company* effects. In turn, we categorise these under two headings. First, governance and culture and second, organisational structure and strategies.

The importance of corporate governance in mutual fund companies has attracted increasing attention in the literature over the last decade following a number of scandals involving well-known firms[43]. Further reflecting this importance and interest, Morningstar introduced a stewardship rating for funds in 2004. Strong corporate governance means unprofessional manager conduct is corrected, investor interests are protected and employee performance is

[43] As detailed by Gottesman and Morey (2012), in December 2006, Deutsche Bank agreed to pay $208 million in order to end federal investigations into their late-trading and market-timing activities. This was the 21st settlement with a mutual fund company made by the Office of the New York Attorney General over the three preceding years.

incentivised – all supporting improved fund performance, alleviating investor concerns and encouraging capital inflows.

The most common organisational structure is a fund family where a single fund management company offers a wide range of funds under alternative categories such as investment objective or fees. Families often offer low-cost switching options between funds for investors. The more families are able to differentiate themselves in terms of nonperformance-related characteristics, the less they need to compete in terms of performance (Massa, 2003). A family structure facilitates strategic behaviour by the fund management company such as allocating attractive investment opportunities such as IPOs to high-value (high-fee) funds within the family or shifting risk between funds and may give rise to family 'tournaments', i.e. intra-family competition. Other strategic behaviour discussed in the literature includes mergers and acquisitions and fund incubation. M&As are often motivated by a desire to expand product offerings in order to increase assets under management (AUM) and hence market share and fees. We now discuss some of the key contributions to the literature in these areas.

Governance and Culture

As mentioned, Morningstar, a well-known mutual fund data provider, now assigns a stewardship rating to funds (since 2004). Stewardship ratings are assigned based on governance factors including board quality, corporate culture, fees, manager incentives, and regulatory issues. The stewardship ratings measure how well fund companies meet their fiduciary responsibilities. Wellman and Zhou (2007) find a positive relation between stewardship ratings and risk-adjusted performance.

In 2007, Morningstar changed its methodology to make corporate culture the most important criterion in the stewardship rating. Morningstar constructs a qualitative corporate culture rating based on its analysts' impressions of whether the fund is investor or sales oriented, the fund is clear in explaining its investment process and results, key personnel are retained and long tenured, whether funds are closed or allowed to expand and hence increase advisory fees, whether redemption fees are used to discourage rapid trading and whether "soft dollars" are prohibited. Based on these criteria, Morningstar assigns one of five corporate culture ratings to each fund as follows: excellent, good, fair, poor, and very poor.

Gottesman and Morey, (2012) construct a simple variable that quantifies these ratings using a scoring system from 5 (excellent) to 1 (very poor). However, the paper finds little evidence that corporate culture predicts better fund performance. In fact, no individual component of the Morningstar stewardship rating including board quality, fees, manager incentives and regulatory issues is able to predict fund performance. This is an odd and concerning finding, although one should treat the Morningstar qualitative stewardship instruments in quantitative studies with some caution.

A further area of fiduciary concern that arises in the literature is the behavior of "affiliated funds" of mutual funds (AFoMFs), Bhattacharya, Lee and Pool (2013). Affiliated funds can only invest in the funds within their own family. Instead of investors choosing which mutual funds of the family to invest in, AFoMFs do so on their behalf. Bhattacharya et al. examine whether AFoMFs allocate investor capital within the family based on funds' liquidity needs. The study first divides fund flow to each mutual fund in the family into AFoMF flow and outside investor flow. Sorting funds into deciles based on outside investor flows, the lowest decile (distressed funds experiencing the largest withdrawals from outside investors) has a statistically significantly higher average inflow from its family AFoMFs than any of the other nine deciles. This suggests that group interest may come before fiduciary responsibilities in certain cases.

Organisational Structure and Strategies

In the US as of 2011, there were 471 family funds where the average number of funds per family was 14 and the maximum number of funds in a family was 393[44]. Membership of a fund family provides economies of scale in research costs, advertising, distribution and labour (Nanda, Wang and Zheng, 2004). Families may also bestow preferential treatment on some funds, e.g. the allocation of 'hot IPOs' as investor inflows chase good past performance and family profits are a function of the subsequent fees generated. The preferential treatment of high-fee (high-value) funds may lead to a positive performance-fee relationship[45]. Based on a sample of IPO issues for the 1992 to 2001 period, Gaspar, Massa and Matos (2006) find that fund families allocate more under-priced ('hotter') IPOs to high fee and high past performance funds.

As discussed in section 4, career concerns and other manager incentives impact the risk taking behaviour of managers. This may be further accentuated within fund families where funds compete for resources including salaries, marketing budgets, IPO allocations, performance bonuses etc. As resources are likely to be skewed towards the top-performing (high-value funds), such internal competition may alter the risk taking behaviour of funds over the course of a

[44] See Shin (2014) for further details.

[45] In general, competition should drive price-sensitive investors to switch between funds. However, Khorana and Servaes (2007) find asymmetric price sensitivity: among families that charge above average fees, families that charge lower fees than the competition gain market share. However, low-cost family funds do not lose market share by charging higher fees.

year in an effort to improve their ranking in the family, i.e. there is a family "tournament". Clare et al. (2014) examine US and European fund families separately over the period 1993-2009. In the case of the US fund industry, the authors report that mid-year loser (below median) funds increase risk more than mid-year winner funds, although the opposite result is found in the case of the fund industry in Europe.

Kempf and Ruenzi (2008) examine US mutual funds between 1993 - 2001 and find that, based on mid-year ranking, the worst fund managers from large families increase risk by 1.83 percentage points more than the best fund managers. This effect is more pronounced for single-managed funds than for team-managed funds.

Mutual fund returns are more closely correlated within than between fund families (Elton, Gruber and Green, 2007). As investors typically restrict investment to one fund family, they are less diversified than they would be if they invested across fund families. Elton et al. report that within families, return commonality is due to common stock holdings and similar exposures to economic sectors and industries.

Fund investors value a high level of product differentiation (based on alternative investment styles, fees and risk levels) as well as low cost switching options between funds (Massa, 2003). Large fund families are better able to provide for such investor needs through strategies such launching more start-up funds, fund incubation and merger and acquisition (M&A) activity, all of which create economics of scale and are an effective means of gaining market share (Khorana and Servaes, 2007).

Luo and Qiao (2013) find that large and complex fund families (as measured by the number of alternative investment objectives funds) are both likely to acquire and also to be a target in M&A activity. In addition, funds experiencing losses of market share to rivals are also likely to be a target. On post-M&A performance during the 2001-2010 period, the authors report that M&As cause a deterioration in the performance of both the acquired funds (that remain independent) and the acquiring company's existing funds[46]. On acquired funds, the performance deterioration is most evident in the funds the acquiring companies are acquainted with due to already having funds with a similar investment objective - acquiring companies reorganize the acquired funds using similar existing funds as a prototype and this reorganization is costly. The performance deterioration in the acquiring company's existing funds may be due to a shift in focus towards the newly acquired funds.

[46] "Independent" means the fund is not merged with an existing fund of the acquiring company.

Fund manager behavioural biases (section 4) are presumed to be driven by *individual* psychological and cognitive biases arising from human emotions such as fear and greed as well as the adoption of heuristic processes. We may be able to gain a deeper understanding of the effects of these biases by investigating whether they are compounded or diminished in a fund family or team setting. For example, we documented previously that poor performing managers in fund families subsequently increase risk relative to top managers. This is consistent with the downward sloping half of the U-shaped relative risk - prior performance relation reported by (Hu et al 2011) but it is not consistent with the upward sloping half.

Incubation

In a strategy known as incubation, fund management companies commence multiple new funds privately for an initial evaluation period after which the more successful funds are offered to investors while the others are closed. Incubation may be a strategy by fund companies to identify superior managers or investment strategies. In a sample of newly created US domestic equity funds from 1996 to 2005, Evans (2010) finds approximately 23% of new funds were incubated and these funds outperformed non-incubated funds annually by 3.5% on a risk-adjusted basis during incubation. However, incubation imparts a survivorship bias in performance analyses as the funds that are closed and not offered to investors are typically not considered. Furthermore, Evans finds a reversal of the outperformance of incubated funds post-incubation.

Overall, corporate culture and fiduciary responsibility are difficult to measure but the few extant attempts to do so suggest they do not positively underpin fund performance as much as one might expect, or hope. Mutual fund organisational structure and strategies are found to play an important role in influencing funds' risk taking and performance. The fund family structure has emerged due to the benefits it yields for mutual fund companies. It bestows significant economies of scale on funds and provides the product differentiation sought by investors. This helps fund management companies grow market share and assets under management - upon which fees are based.

There is evidence that *within* fund families some funds receive preferential treatment in terms of, for example, the allocation of hot IPOs. These are higher fee funds whose superior performance then attracts inflows. Although this suggests the fund management company acts strategically across funds, there is also evidence of intra-family tournaments between funds. This manifests itself in poorer performing funds subsequently increasing risk in a bid to catch up - motivated by intra-family competition for resources, not least salaries and bonuses.

Merger and acquisition activity among fund companies is largely motivated by economies of scale and as a means of offering product differentiation to investors (e.g. wider variety of investment style offerings). However, there is evidence that M&As cause a deterioration in the performance of both the acquired funds as well as the acquiring company's existing funds.

6. CONCLUSION

The evidence on *ex-ante* sorting rules to predict future fund performance is voluminous, yet attempting to give a brief yet balanced summary of *ex-ante* predictability across US and UK studies is difficult. After noting the many caveats, it may be that there are some multiple sorting rules (with monthly rebalancing) that result in positive 4F-*gross* alphas – so a portfolio comprising a "revolving set" of skilled funds earns *ex-ante* positive gross abnormal returns. However, this does not in general result in *ex-ante* positive 4F-net alphas for investors, as they switch between alternative fund portfolios - even before taking account of switching costs such as load fees, advisory fees and time costs. Finding successful funds *ex-ante* is extremely difficult, if not impossible. In contrast, there is strong evidence that poor performance persists for many of the prior "loser fractile" portfolios of funds.

There is a high degree of employment risk for mutual fund managers as dismissal is often preceded by prior poor performance. A strong theme in the literature is that relatively poor performance is followed by relatively high risk taking - largely as a gamble to "catch up" with one's peers. Some influential studies report a U-shaped relation between past performance and risk taking where top funds also subsequently increase risk – there is evidence this is due to an overconfidence effect. Also, within fund families, there is evidence that low ranked funds by mid-year also take on greater risk in the second half of the year (compared to top funds). This is due to intra-family tournaments where funds are in competition for resources such as advertising and marketing budgets, salaries and bonuses.

It is well established that investor inflows respond strongly to past good fund performance but are *relatively* insensitive to past poor performance. This convex relationship influences the behaviour of fund management companies because fees depend on assets under management.

The convex fund flow-performance relationship gives fund management companies an incentive to transfer risk from high-performing to poor-performing funds. If the risky bets pay off, then inflows are greater than any outflows if the risky bets fail. We see this in intra-fund family tournaments where low ranked funds by mid-year take on greater risk in the second half of the year compared to top funds. Similarly, there is evidence that fund management companies give preferential treatment to high-value (high-fee) funds in the family in terms of allocating hot IPOs. The resulting expected superior performance is expected to attract greater inflows than the outflows from the 'neglected' funds. It has also been found that factors that increase (decrease) the convexity of the fund flow-performance relationship also increase (decrease) the convexity of the U-shaped risk-prior performance relation.

The literature identifies several manager behavioural biases that impact, usually negatively, on fund returns and risk taking. Chief among these are herding, home bias, a disposition effect, overconfidence and window dressing. Not surprisingly, some manager characteristics (as well fund characteristics) also explain the cross-section of fund performance. In particular, the quality of the undergraduate institution attended by the manager may have a positive effect on performance. However, neither MBA nor CFA qualifications are found to be robust predictors of performance.

Investors exhibit a high degree of inertia when switching out of poorer performing funds and this is exploited by fund management companies. To the extent that investors do switch out of funds, fund management companies such as fund families now typically offer low cost switching options for investors to stay in the same family. Evidence also shows that the majority of investors only hold mutual funds in one family. As fund returns within a family exhibit relatively high correlation, investors are less than optimally diversified.

In summary, the literature on mutual fund management has established that manager behavioural biases are pervasive and reduce performance. As such there is an onus on mutual fund management companies to demonstrate good corporate governance, to monitor manager's behaviour and protect their investors. While the risk management functions of fund management companies are sophisticated operations, more could be done in acting on the clear findings around manager behavioural biases.

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