Fund Manager Overconfidence and Investment Performance: Evidence from Mutual Funds

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Abstract

The purpose of this paper is to investigate to what extent mutual fund managers, as an important and representative group of professional investors, are prone to overconfidence and associated behavioural biases such as self-serving attribution. More importantly, we explore how these psychological attributes may have any bearing on investment performance. The fundamental question is why, how, and through which mechanisms does overconfidence affect investment performance, if at all. We measure managerial overconfidence by content analysing the narratives of reports fund managers write to their investors, and by using a range of proxies including overoptimism, excessive certainty and excessive self-reference. We study a large sample of US actively managed equity mutual funds during the 2003-09 period. The cross-sectional variations in this sample demonstrate that superior past performance boosts managerial overconfidence as measured by a number of proxies. Importantly, our findings also suggest that excessive overconfidence is associated, to a large extent, with diminished future investment returns in the 12 months following the publication of the annual report. This effect is robust across different investment styles, although it appears to be stronger among growth-oriented funds. A closer investigation reveals an overall inverted-U relationship between fund manager overconfidence and subsequent investment performance. Furthermore, a hedging strategy based on shorting funds with abnormally overconfident managers and going long in funds with normally confident managers yields positive average returns after controlling for Carhart factors.

Keywords: fund manager behaviour, overconfidence, mutual fund performance, investor psychology

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1. Introduction

Traditional finance uses theoretical models that predominantly assume economic agents are rational, i.e. efficient and unbiased information processors who constantly seek to maximise their utility. It is now widely agreed that these appealingly simple assumptions are quite inaccurate (see e.g., Barberis and Thaler, 2003). Behavioural finance, on the other hand, assumes that investors are often subject to behavioural biases that can negatively affect their financial decisions. These biases and heuristics, which are typically grounded in the cognitive psychology literature, are being increasingly applied in financial contexts. Indeed, studies in behavioural finance often lead to conclusions that significantly resonate with what professionals in the finance industry experience and "know" at a deeper and perhaps unconscious level (Taffler and Tuckett, 2010). In this way, behavioural finance has revolutionized the way we think about investments.[1]

In this context, studying investor psychology is of paramount importance. Hirschleifer (2001), among others, provides a detailed survey of studies linking investor psychology to asset pricing and argues that this issue lies at "the heart of the grand debate in finance spanning the last two decades." While a complete understanding of investor psychology requires familiarity with a wide range of individual and group behaviours, a few psychological traits are often recognized as highly influential in shaping investors decisions. The overconfidence effect clearly belongs to this list.

The overconfidence effect, due to its broadness and importance, has been widely influential outside the field of psychology (see Daniel, Hirshleifer and Subrahmanyam, 1998; Santos-Pinto and Sobel, 2005; Statman, Thorley and Vorkink, 2006; and Garcia, Sangiorgi and Urošević, 2007 among others). The role of overconfidence in influencing the behaviour of economic agents and, by extension, the functioning of financial markets, is an emerging, increasingly important and widely researched topic.[2] In fact, it has been suggested that in the field of judgment and decision-making, no problem is "more prevalent and more potentially catastrophic than overconfidence" (Plous, 1993).

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[1] This change of paradigm from a framework based on neoclassical assumption to one based on psychological assumptions is still an ongoing and highly dynamic process. Shefrin (2009) discusses this issue and provides a detailed review of the strengths and weaknesses of both approaches.

[2] In a search conducted in January 2011, we found 1,517 peer-reviewed journal articles published between 2000 and 2010 in *Business Source Premier*, a major literature database, that contain the keyword "overconfidence". Almost half the total number of articles (724 items) were published after 2007, clearly showing a rising trend. A search in the *ScienceDirect* database yielded similar results.

To properly understand overconfidence, it is appropriate to start from the closely related concept of "optimism". Optimism seems to be an integral part of the human psyche. From the perspective of evolutionary processes, it is proposed that optimism must have brought the early humans important benefits, and therefore, in the course of thousands of years of evolution, it has become part of the genetic hardwiring of our brains.[3] Apart from this evolutionary perspective, it is now widely known that humans constantly learn about themselves and their abilities by observing the consequences of their actions. In doing so, most people overestimate the degree to which they play a role in their own successes. This tendency is often amplified by an illusion of control, i.e. by thinking that one can control or influence an outcome. The overconfidence resulting from this mechanism can have several negative consequences for decision-making, as we will discuss in detail in the literature review. In fact, many researchers cite overconfidence as an explanation for wars, strikes, litigations, entrepreneurial failures and, not surprisingly, stock market bubbles (Glaser, Noth and Weber, 2007; Moore and Healy, 2008).

A large body of literature has more recently focused on the overconfidence of corporate managers, and its impact on corporate investment decisions in areas such as capital structure and M&A activity (see Malmendier and Tate, 2005; Malmendier and Tate, 2008; Malmendier, Tate and Yan, 2011; and Gervais, Heaton and Odean, 2011 among others). The questions asked in this paper, however, concern the impact of overconfidence on professional investors, which is a far less studied research area. The underlying research questions are motivated by three large areas of literature, i.e. studies of mutual fund performance and persistence, studies of financial accounting narratives and business communication, and studies of professional investor psychology. In particular, the following research questions are asked in this paper:

1. How does a fund manager's prior investment performance affect her state of mind, and particularly overconfidence?
2. To what extent, if at all, does a fund manager's overconfidence impact the subsequent investment performance of the funds he manages?
3. Can what we know about fund manager overconfidence help investment companies recruit more "successful" managers?

In essence, this paper seeks to investigate the dynamic relationship between fund-manager expressed overconfidence and the investment performance of a mutual fund. The areas of focus are the extent to which (1) fund manager overconfidence impacts the fund's future investment performance and (2) the dynamics of this complex relation across fund type, investment style, fund manager duration and the proxies used to measure overconfidence. We

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[3] Our early ancestors who had to leave their caves in the very hostile environment of African savannahs to hunt for food in competition with the wildest predators, did in fact require optimism, and perhaps even some level of overconfidence to take that first step.

use the well-known Carhart asset-pricing model as the basis of an empirical model which we seek to improve by adding independent variables proxying for fund manager psychological attributes. The paper includes controls for other potential confounding factors, and tests the overall robustness of the empirical model. We specifically test the following null hypothesis:

- There is no significant difference in the future investment performance of mutual funds whose managers exhibit varying degrees of *optimism/certainty/self-reference* in their annual reports to investors, ceteris paribus.

As financial agents, professional investors often operate in an environment that is significantly different from the assumptions of conventional models. Conventional finance views financial agents in terms of "rational" actors in the marketplace who use formal methods of asset valuation in an attempt to identify those stocks or other assets which may be mispriced; even though, on the other hand, markets are viewed traditionally as efficient. In contrast, the world of the *real* investment manager is one where she is swamped by information, is subject to acute information asymmetry, is under intense competition, and, in the end, has to rely to a large extent on subjective judgment, intuition and "gut feeling". Added to this are the many imponderables which are outside her control, may largely drive her investment performance, and are intangible from an external viewer's perspective (Holland, 2009). Ultimately, the professional investment manager is required to do a job which is very difficult if not impossible to do, and is under constant threat of dismissal if the returns she earns are not deemed satisfactory.

We argue that such environmental forces can, in a subtle way and through time, feed into professional investors' overconfidence, and indirectly affect how they make investment decisions. Specifically, such features of financial markets, together with investors' past performance results and their personal attributes, can breed or diminish overconfidence, which, as this paper argues, may affect investment performance in several ways.

This paper attempts to take a mixed methods research approach. Prior research has found significant potential in applying mixed methods research strategies in the accounting and finance domain. The key strengths of mixed methods research include both testing and building theories through extension of existing theories as well as convergence and contradiction of findings. A closely related concept is that of methods triangulation which is often defined as "the use of more than one research method as part of a validation strategy to ensure that the explained variance is the result of the underlying phenomenon and not an artefact of the research method adopted" (Campbell and Fiske, 1959). This paper mainly seeks to adopt a between-methods approach although each of the qualitative and quantitative sections consists of several elements.

Our paper is organised as follows: Section 2 introduces the core constructs and variables and discusses the issue of measuring overconfidence. Section 3 introduces the data and its sources, and provides relevant descriptive statistics. Section 4 uses a number of empirical methods to explore how fund manager overconfidence and associated measures may impact future investment performance. Finally, section 5 concludes the paper, and discusses research implications as well as areas for further work.

2. Conceptualizing and measuring overconfidence

The terms "confidence", "trust" and "full belief" are usually considered synonyms. In fact, "confidence" is derived from the Latin *fido* meaning "I trust". The credit crisis we have just witnessed may be also known as a confidence crisis and it is interesting to observe that "credit" is similarly derived from the Latin *credo* meaning "I believe". The level of collective trust and confidence among investors can demonstrably have significant impacts on financial markets. Humans constantly learn about themselves and their abilities by observing the consequences of their actions; and in doing so, most people overestimate the degree to which they play a role in their own successes.[4]

A number of constructs need to be clearly differentiated in this discussion. Van den Steen (2002) provides a comprehensive categorization for this purpose: *Self-serving attribution* bias refers to the fact that people attribute success to their own dispositions and skills, while they attribute failure to external forces or bad luck; ego-centric or *self-centric* bias refers to the fact that individuals taking part in a joint endeavor relatively over-estimate their contribution to a good outcome; *overconfidence* relates to the fact that people over-estimate the accuracy of their estimates and predictions; *overoptimism* refers to the fact that individuals tend to be overoptimistic about future events and the consequences of their actions; and finally, *illusion of control* relates to the fact that people think they have more influence than they actually do over the outcome of a random or partially random event.

Prior psychology literature has produced two different types of explanation for overconfidence and its associated effects. From one perspective, these phenomena have been interpreted in the context of motivational biases, the argument being that individuals are motivated to hold unrealistically positive self-perceptions in order to increase their own happiness and well-being. The core assumption is, of course, that people seek to maximize their happiness in a utilitarian way. Alternatively, a different perhaps complementary view is put forward by cognitive psychologists who argue that people generally expect to succeed, and they often accept responsibility for their expected outcomes. Hence, in combination of the two effects, people tend be prone to self-serving attribution bias.

Importantly, the self-serving attribution bias can, in turn, produce overconfidence. Gervais and Odean (2001) explain that investors may falsely attribute superior past performance to their own skill, and inferior past performance to chance, which produces overconfidence. Overestimation of one's investment skill can, in this manner, result in excessive trading, as

[4] This effect has been extensively studied in the psychology literature. A number of key papers in this relation are cited in Gervais and Odean (2001).

documented by Odean (1999). Despite the extensive literature examining attribution and overconfidence among ordinary individuals, corporate executives, traders, and retail investors, there are few studies that can claim to have examined the role of such biases in subsequent fund manager performance. In particular, due to the fact that the bulk of investment in financial markets is made by institutional investors, any link between a professional asset manager's performance and her potential overconfidence or susceptibility to attribution bias can be of considerable importance, both to the academic literature and the investment industry.

The overconfidence effect, in a general context, is often measured in psychology through laboratory-type experiments (see Hoffrage (2004) for a good review). However, few of these experimental approaches are robust when it comes to gauging investor overconfidence, not least because of issues concerning ecological validity. Thus, researchers often resort to indirect effects proxying for overconfidence among investors. For example, trading activity is a commonly used proxy of investor overconfidence (Barber and Odean, 2000). However, while this measure clearly works for retail investors, it cannot be as easily used for fund managers. Fund managers do not always engage in excessive trading due to overconfidence, rather they may have to increase their turnover after a rise in fund inflows, which usually follows good past performance. Putz and Ruenzi (2009) control for this effect in their examination of the turnover of US equity mutual funds over the period 1994-2004. The authors conclude that fund managers indeed trade more after good past performance, and their higher trading is driven by individual portfolio performance. This is consistent with superior past performance producing task-specific overconfidence. In a similar way, Chow, Lin, Lin and Weng (2009) examine a sample of equity mutual funds, and show that fund managers behave overconfidently conditional on prior performance. They also demonstrate that such behaviour deteriorates subsequent performance. However, one should note that other potential confounding factors may affect managerial trades, such as incentive for window-dressing, tax-management issues, preference for liquidity and changing investment styles to attract fund flows, thus reducing the robustness of trading activity as a proxy for overconfidence.

Another proxy recently used in the literature for measuring overconfidence is *Active Share*. Active Share refers to the share of portfolio holdings that differ from benchmark index holdings, and is introduced as a new measure of active portfolio management by Cremers and Petajisto (2009). Using this measure, Choi and Lou (2008) are able to show that mutual fund managers are typically susceptible to the self-serving attribution bias. However, Active Share is not a "clean" measure of overconfidence either. A similar set of confounding variables can influence the way fund managers choose to arrange their portfolios. In addition, defining the optimal benchmark portfolio against which to measure Active Share is not trivial.

A more straightforward way of measuring overconfidence may, of course, be to examine the actual estimates and predictions of fund managers about their subsequent performance. Willis (2001), for examples, investigates annual earnings forecasts that are publicly released in conjunction with mutual fund manager stock recommendations, thereby finding evidence of excess optimism. Gort, Wang and Siegrist (2008) examine overconfidence using a similar method, and conclude that the pension fund managers in their sample provide too narrow confidence intervals when asked to forecast future returns or estimate past returns of various assets. However, since their approach requires questionnaire-type surveys attempting to measure fund manager confidence intervals, it cannot be readily used for a large sample of respondents and is subject to the usual robustness concerns associated with this type of secondary data collection.

In this research, we suggest a novel approach to measuring professional investor overconfidence. We use three proxies in measuring overconfidence: overoptimism, excessive certainty and excessive self-reference. The *Diction* software is used to extract the first two variables. Diction is a well-known content analysis software that is widely used in the field of finance and accounting, among other fields, to produce consistent narrative-based scores for any given text. Diction has been used extensively to analyze the speeches of policymakers, political speeches, earning announcements and corporate annual reports. The algorithm uses a series of thirty-three dictionaries (word-lists) to search text passages for different semantic features such as, e.g., praise, satisfaction, or denial. In this study, we predominantly use the optimism and certainty master variables.

In Diction, optimism is defined as, "language endorsing some person, group, concept or event or highlighting their positive entailments." The formula used for calculating "net optimism" is: *[praise + satisfaction + inspiration] - [blame + hardship + denial]*; in other words, "optimism" minus "pessimism". Diction defines certainty as "language indicating resoluteness, inflexibility, and completeness and a tendency to speak ex cathedra." The Diction formula for certainty is: *[tenacity + leveling + collectives + insistence] - [numerical terms + ambivalence + self reference + variety]*. We use the adjustment proposed in Demers and Vega (2010) to include numerical terms as adding to rather than subtracting from the certainty score.

The third proxy used in this paper for overconfidence is self-reference which is defined as the normalized frequency of first-person singular and plural pronouns in each narrative (I, me, my, mine, we, us, our, ours), which can be derived from Diction with a simple calculation. We also explore the possibility of constructing a meta-variable comprising some or all of the overconfidence proxies. Since the face validity of these variables is an issue that can be discussed in detail, the usefulness of such overconfidence meta-variable will be evaluated on an empirical basis.

3. Data

This section provides information about the sources as well as a general outline of the data used in this study. The mutual fund performance data used in this research is sourced from the CRSP Survivor-Bias-Free Mutual Fund Database. This database, widely used in the finance and accounting literature, is designed to facilitate research on the historical performance of open-ended US mutual funds. It claims to be "the only complete database of both active and inactive mutual funds" and distinguishes itself by providing survivor-bias-free data. The database was initially developed by Mark Carhart for his 1995 dissertation entitled, "Survivor Bias and Persistence in Mutual Fund Performance", to fill a need for survivor-bias-free data coverage which was previously lacking. Incidentally, the key regression model used in the current study is based on Carhart's (1997) seminal paper.

The mutual fund annual reports used in this study are derived from the EDGAR database. EDGAR (hereinafter Edgar) stands for the Electronic Data-Gathering, Analysis, and Retrieval system and is a publicly available database provided by the US Securities and Exchange Commission (SEC). It performs automated collection, validation, indexing, acceptance and forwarding of submissions by companies and, in some cases, individuals who are legally required to file forms with the SEC.

While most companies need not submit actual annual reports to shareholders on Edgar, it is a mandatory requirement for mutual fund companies to do so. For other companies, however, the annual report on Form 10-K containing much of the same information is required to be filed on Edgar. These requirements make Edgar an excellent source of annual reports for all US companies regardless of industry sector.

A word about the issue of authorship of mutual fund annual reports is relevant: Firstly, according to the conventions in the mutual fund industry, fund managers often write their own reports and commentaries which may then be edited by in-house writers only to check correct spelling and grammar, and to ensure presentational consistency with other sections of the annual report. In other words, the in-house editors are mostly concerned with the professional presentation of the annual report as a whole document and are much less concerned with the core thematic elements, sentence structure and other rhetorical features of the fund manager narratives. Secondly, similar to the prevailing practice in CEO communications, fund managers are signatories of their reports and assume legal responsibility for their content. Amernic, Craig and Tourish (2010) argue that this acts as an incentive for them to closely scrutinise and approve the final version of the narrative before signature and publication. More importantly, they argue, "whether or not a CEO is actively involved in composing a letter to stockholders does not matter: the words in the CEO's letter are symbolic and emblematic, and the reader takes them to be the CEO's own." Clearly, a similar proposition can be made about fund managers. And finally, to what extent mutual fund manager narratives are linked with investment performance is inherently an empirical question, regardless of the subject of authorship.

The question of authorship of fund manager reports can be further examined by investigating the variations between individual fund manager reports within the same investment company. This is because if we assume that the content of fund manager reports and the writing style of fund managers are substantially influenced by the overarching investment philosophy of the organisation in which they operate or the role of in-house writers, one should expect to find a homogeneous set of narratives in each company's annual report regardless of who the fund manager is. This, however, does not appear to be the case. In order to study the extent of cross-sectional variation in fund manager reports, in a pilot study I examined 50 mutual fund reports randomly selected from 5 different investment companies. The results of cross-comparisons across a range of Diction variables as well as readability and tone indicate that there is indeed a significant level of within-sample variation that can be attributed to individual fund manager characteristics. Clearly, a more robust test that would control for the types of funds in cross-comparisons can further confirm this observation.

We begin by exploring the Edgar database in 2009 and look for all mutual fund filings made during this year. We systematically search for all mutual fund annual reports filed in the form N-CSR (Certified Shareholder Report of Registered Management Investment Companies).[5] As expected, most annual reports are filed in the first quarter. In fact, about 45% of the annual reports are typically filed in the first quarter and about 25% during the last quarter of the calendar year. The remaining 30% of annual reports are filed during the second and third quarters. We exclude amended disclosures. Therefore, by looking at one full year, we acquire the whole annual set of unique mutual fund reports regardless of whether they correspond the current or previous fiscal year. Next, we match the CIK identifier of the annual reports with the corresponding CUSIP. As explained above, with the help of the fund's name, this often results in a unique matching. Then, we select only those CIKs whose corresponding CUSIPs belong to actively managed equity mutual funds.

We use the CRSP fund information to control for fund manager changes. We limit our sample to funds having complete returns data and a unique fund manager for at least three consecutive years. The *mgr-dt* variable provided by the CRSP database marks the date the current portfolio manager assumed responsibility for the portfolio. Since our whole sample consists of 2003-2009 annual reports, we initially exclude all funds whose *mgr_dt* variable predates 1 January 2006. Then, we repeat the same process for those annual reports filed during 2008 that have not been filed in 2009, and add the corresponding distinct mutual funds to the sample. We continue this process until we cover *all the actively managed equity mutual funds with a unique manager and complete returns data for at least three consecutive years during the 2003-09 period*. Finally, we remove from our sample the annual reports with no substantial fund manager commentary (i.e. less than 200 words). Table 1 illustrates the above sample selection procedure.

[5] Mutual funds also file semi-annual reports with SEC in the form N-CSRS which are excluded in this study.

Table 1: The sample selection procedure

Mutual fund annual reports filed in Edgar during 2009	3319
Less amended annual reports (N-CSR/A)	*166*
Unique mutual fund annual reports filed in Edgar during 2009	3153
Less annual reports with no corresponding CUSIP match	*224*
Less bond funds, money market funds and index funds	*380*
Active equity mutual fund annual reports filed in 2009	2549
Less annual reports with a change of the corresponding fund manager or missing returns data during 2006-09	*831*
Active equity mutual funds with unique managers and full returns data during 2006-09	1718
Repeat the above process for the 2005-08 period and add corresponding distinct funds	1421
Repeat the above process for the 2004-07 period and add corresponding distinct funds	1255
Repeat the above process for the 2003-06 period and add corresponding distinct funds	977
Active equity mutual funds with unique managers and complete returns data for at least three consecutive years during 2003-09	5371
Less mutual funds with missing or no significant fund manager commentary in the corresponding annual reports	*712*
Main sample	**4659**

Hence, for the purpose of our panel data analysis, we arrive at 4659 unique actively-managed equity mutual funds that have had a unique fund manager and complete returns data for at least three years during the sample period, and have corresponding fund manager commentaries. This yields the main sample for most of the empirical tests in this paper.

Table 2 reports summary statistics on the total actively-managed equity mutual funds that have a corresponding CUSIP match in the CRSP database. The statistics provided are related to the annual performance on an absolute basis, fund size, expenses and turnover. Definitions of these measures are also listed.

Table 2: Summary statistics of the sample mutual funds

Absolute Return: Daily, monthly and annual returns values are calculated in CRSP as a change in NAV (net asset value) including reinvested dividends from one period to the next. NAVs are net of all management expenses and 12b-1 fees.[6] Front and rear load fees are excluded. **TNA**: Total Net Assets as of the last trading day of each month, figures are averaged for each year. **Expense Ratio**: Expense Ratio as of the most recently completed fiscal year. It represents the ratio of total investment that shareholders pay for the fund's operating expenses, which include 12b-1 fees. **Turnover**: Fund Turnover Ratio. It is defined as the minimum of aggregated sales or aggregated purchases of securities, divided by the average 12-month Total Net Assets of the fund.

Year	Number	Average Return (% per year)	TNA ($m)	Expense Ratio (% per year)	Turnover (% per year)
2003	2169	30.2	295.2	1.5	86.3
2004	2201	38.0	336.6	1.6	91.9
2005	2287	32.6	385.0	1.4	105.2
2006	2490	25.4	439.9	1.5	92.0
2007	2355	-18.9	485.2	1.5	133.6
2008	2612	-25.1	377.6	1.3	125.6
2009	2549	-10.6	441.4	1.4	108.7
Mean	2380	10.2	394.4	1.5	106.2
Median	2355	25.4	385.0	1.5	105.2
SD	173	27.2	65.9	0.1	18.9

We specifically look at *optimism*, *certainty* and *self-reference* of fund manager commentaries to infer the overconfidence of their corresponding managers. Table 3 summarises the descriptive statistics provided there for the research variables used in this study based on the main sample.

[6] 12b-1 fee denotes the ratio of the total assets attributed to marketing and distribution costs. It represents the actual fee paid in the most recently completed fiscal year as reported in the Annual Report Statement of Operations.

Table 3: Descriptive statistics of overconfidence proxies

This table reports the distribution of selected overconfidence proxies based on the content analysis of fund manager narratives, as well as positive/negative tone and readability. Optimism and certainty are computed by Diction, and certainty is adjusted according to Demers and Vega (2010). The optimism scores are based on the fund outlook section, the self-reference scores are based on the past-performance discussion section and certainty scores are based on the whole narrative.

	Mean	SD	Min	1st Quart	Med	3rd Quart	Max
OPTIMISM	52.20	2.11	43.50	49.28	51.58	55.42	64.16
CERTAINTY	47.25	1.37	44.39	46.14	46.92	48.15	51.97
SELF-REFERENCE	1.13	0.18	0.74	0.99	1.04	1.28	1.76

Figure 1 provides a simple histogram for optimism scores in a typical year by averaging the distributions of the scores across the sample years. The shape of the histogram, as well as the mean and median values in Table 3, indicate that there is a small positive skew in what is a largely normal distribution. In addition, the instances of extreme (outlier) fund manager overconfidence are more common than underconfidence. This can be due to the fact that fund manager selection processes that are in operation in the investment industry, which often include an interview with the fund manager to be recruited (Goyal and Wahal, 2008), are biased in the favour of overconfident managers. A similar distribution exists for the certainty and self-reference measures.[7]

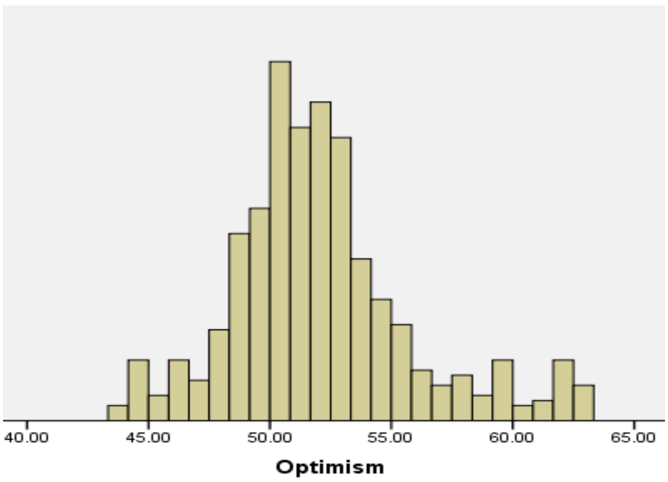

Figure 1: Histogram of the distribution of fund manager optimism scores during an average sample year

[7] The overconfidence scores are winsorized at the 5% level (i.e. 90% window) for the main tests in this paper.

Table 4 reports Pearson's correlations between the overconfidence measures derived from the narratives and the risk factors embedded in the Carhart asset pricing model based on the same sample.

Table 4: Cross-correlation matrix for study variables

	Optimism	Certainty	Self-reference	$R_M - R_F$	SMB	HML	MOM
Optimism	1.00						
Certainty	0.416	1.00					
Self-reference	0.755	0.488	1.00				
$R_M - R_F$	0.228	0.093	0.106	1.00			
SMB	0.163	-0.054	0.215	0.197	1.00		
HML	0.101	-0.118	0.147	-0.255	-0.173	1.00	
MOM	**0.370**	**0.292**	**0.366**	0.084	0.339	0.305	1.00

Importantly, the cross-correlations between the overconfidence proxies suggest that optimism and certainty are to some extent associated measures of overconfidence and they are both positively correlated with momentum (previous one-year return), i.e. a fund manager experiencing positive prior returns is likely to grow more optimistic about her future performance as well as more resolute in her tone of voice. There is a also significant correlation between optimism and self-reference which is consistent with the expectations and the empirical evidence demonstrated in this paper.

In addition, the relatively low correlations between the proxies and the Carhart risk factors are promising since they suggest that fund manager overconfidence, as measured here, is not directly driven by any intrinsic fund characteristics and associated risk factors. Particularly in the case of momentum, one can argue that a large part of the variation in optimism is not explained by momentum. In other words, the implication is that our overconfidence measure has a good chance of capturing an effect distinct from other previously studied factors that influence investment performance.

4. How does overconfidence affect future investment performance of mutual funds?

In this section, we test the hypothesis that excessive levels of overconfidence interfere with sound investment decision-making and thereby diminish future investment returns. In other words, we expect that a fund manager with higher levels of net overconfidence (after considering the effect of prior performance) may experience lower future returns, everything else held constant. Therefore, the general null hypothesis can be formed as follows:

> "There is no significant difference in the future investment performance of mutual funds whose managers exhibit varying degrees of overconfidence (proxied by overoptimism, excessive certainty and excessive self-reference), *ceteris paribus*."

We use the well-known Carhart model as the base regression model to test the research hypotheses in this paper. The Carhart (1997) model builds on the Fama-French three-factor model by adding prior-year momentum which, for the purpose of this paper, adequately captures the effect of previous performance. Therefore, the general approach would be to add the overconfidence measure as independent variable to the Carhart model, and then to regress the average monthly returns subsequent to the publication of the annual reports accordingly.

$$E(R_{it}) - R_{ft} = \beta_0 + \beta_{1i}[E(R_{mt}) - R_{ft}] + \beta_{2i}E(\mathrm{SMB}_t) + \beta_{3i}E(\mathrm{HML}_t) + \beta_{4i}E(\mathrm{MOM}_t) + \beta_{5i}E(OC_t)$$

We use two empirical approaches to investigate this effect: the *portfolio-tracking* approach and the *calendar-time* method.

4.1. The Portfolio-Tracking approach

In this section, we use the *portfolio-tracking* empirical approach to test the research hypotheses. Generally, the portfolio-tracking method requires the funds to be sorted based on a given parameter into decile portfolios. Then, portfolios of extreme deciles are formed, and the monthly returns series are followed using an appropriate asset-pricing model (the Carhart model in this case). Subsequently, the Carhart factors of the extreme portfolios are compared each year, and then the portfolios are rebalanced annually.

Following this methodology, we rank our sample funds based on their OPTIMISM, CERTAINTY, and SELF-REFERENCE scores in each year and form 10 equally weighted decile portfolios for each of the sample years between 2003 and 2009. Since about 45% of the annual reports are typically filed during the first quarter and for reasons of consistency, we perform the portfolio sorts in the end of March in each year.[8] Following this ranking

[8] There is a large body of accounting literature that investigates the issue of delay in reporting, and further research can look at this issue in the context of mutual fund annual reports to gain a better understanding of any potential strategic behaviour by investment companies in this area.

month, each portfolio is held for twelve months and the time-series of monthly portfolio excess returns (i.e. average cross-sectional stock returns within each portfolio minus the corresponding risk-free interest rate) is constructed. The portfolio is then reformed at the end of March in the following year and the time series is extended.

In addition, we test a hedge strategy inspired by the research hypotheses in this paper. Are fund managers that express abnormal levels of overconfidence (as proxied by OPTIMISM, CERTAINTY, and SELF-REFERENCE) likely to underperform in the following months since their excessive overconfidence may negatively impact their investment decisions? We construct a long-short portfolio strategy based on shorting the portfolio with the highest level of overconfidence (P10) and going long the portfolio with a lower level of overconfidence. We do the long stage in two ways. In the *Hedge1* strategy, we long the portfolio with the lowest level of confidence (P1) and in the *Hedge2* strategy, we long the portfolio with an average (i.e. "normal") level of overconfidence (P5). Hence, the *Hedge1* strategy captures the P1-P10 returns while the *Hedge2* strategy captures the P5-P10 returns.

Prior studies in accounting and finance as well as other domains (e.g. competitive sports) indicate that underconfidence (diffidence) can have a similarly detrimental effect on decision making and performance, resulting in an inverted U shape when performance is plotted against confidence. Thus, everything else being equal, one might expect the *Hedge2* strategy to capture higher positive abnormal returns compared to the *Hedge1* strategy. In other words, while it is not reasonable to assume that fund managers with the lowest confidence levels are significantly better at making investment decisions compared to overconfident fund managers, "reasonably" confident fund managers (i.e. those with an average, "normal" confidence level) are expected to make better investment decisions compared to their peers and thus produce higher returns, *ceteris paribus.*

In order to test the significance of abnormal returns using the Carhart (1997) four-factor model, we first gain an overall picture by plotting the monthly portfolio excess returns for the extreme portfolios P1 and P10 as well as the intermediate portfolio P5 based on OPTIMISM scores. Results are displayed in Figure 2.

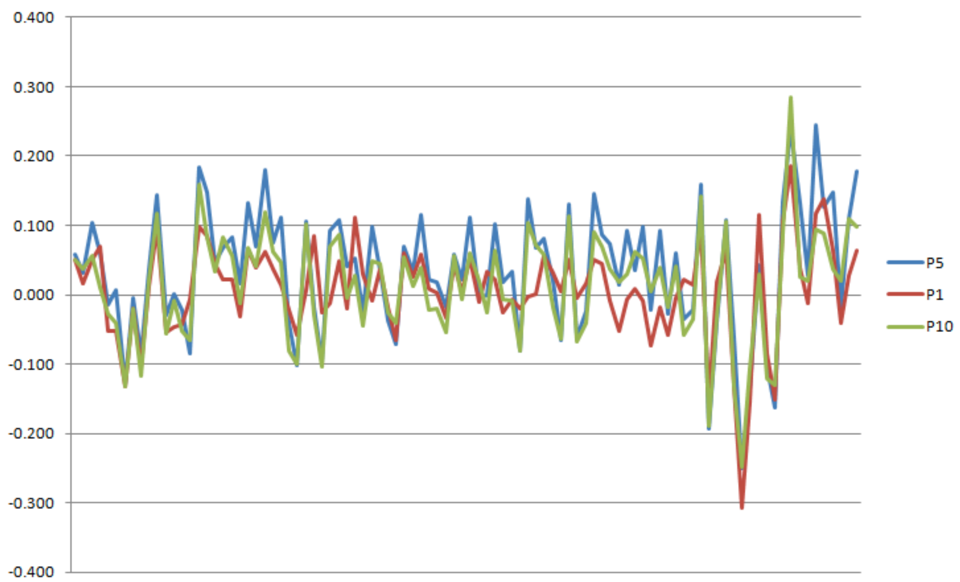

Figure 2: Monthly average excess returns of extreme and intermediate decile portfolios based on OPTIMISM scores

(P1 is the annually ranked portfolio of funds with the lowest OPTIMISM scores, P10 is the annually ranked portfolio of funds with the highest OPTIMISM scores, and P5 is the annually ranked portfolio of funds with intermediate OPTIMISM scores.)

It appears from figure 2 that the monthly excess returns of the extreme decile portfolios co-move to a large extent. However, the monthly excess returns of the intermediate portfolio are slightly out of sync and appear to be marginally higher, which prompts further investigation. Thus, following the portfolio-tracking approach, we perform the required monthly time-series regressions for each portfolio as in Barber and Odean (2001) and Kumar and Lee (2006). Therefore, we use the following equation in Table 5:

$$E(R_{it}) - R_{ft} = \beta_0 + \beta_{1i}[E(R_{mt}) - R_{ft}] + \beta_{2i}E(\mathrm{SMB}_t) + \beta_{3i}E(\mathrm{HML}_t) + \beta_{4i}E(\mathrm{MOM}_t)$$

where i indicates a particular portfolio and t refers to a specific month.

Table 5: The impact of fund manager overconfidence on excess returns, using portfolio-tracking analysis

Sample funds are sorted into decile portfolios based on prior year overconfidence scores for each year, i.e. the funds in each portfolio may change every year based on their manager's expressed overconfidence. Then, equally weighted average return in each month is calculated for the ten decile portfolios. The *Hedge1* returns are the difference between the returns of the top and bottom decile portfolios (P1-P10) and the *Hedge2* returns are the difference between the returns of the top and intermediate decile portfolios (P5-P10). ($R_M – R_f$) is the excess return on the broad market portfolio. SMB is the difference between the return on a portfolio of small stocks and that of large stocks. HML is the difference between the return on a portfolio of high-book-to-market stocks and low-book-to-market stocks. MOM is the difference between the return on a portfolio of high prior return stocks and low prior return stocks.

Panel A: Fund portfolios formed on OPTIMISM scores

	P1	*P2*	*P3*	*P4*	*P5*	*P6*	*P7*	*P8*	*P9*	*P10*	*Hedge1 returns*	*Hedge2 returns*
Rm-Rf	1.067***	1.011***	0.918***	0.933***	1.182***	1.072***	1.005***	0.916***	0.949***	1.052***	0.015***	0.130***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
SMB	0.494***	0.450***	0.397***	0.426***	0.406***	0.401***	0.389***	0.356***	0.337***	0.314***	0.180**	0.092***
	(0.000)	(0.001)	(0.001)	(0.002)	(0.000)	(0.000)	(0.000)	(0.003)	(0.000)	(0.000)	(0.032)	(0.008)
HML	0.644***	0.686***	0.656***	0.589***	0.577***	0.586***	0.578***	0.598***	0.628***	0.551***	0.093***	0.026**
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.018)
MOM	-0.209***	-0.276***	-0.350***	-0.201***	-0.185***	-0.224***	-0.271***	-0.153***	-0.108***	-0.176***	-0.033**	-0.009**
	(0.000)	(0.003)	(0.001)	(0.000)	(0.005)	(0.000)	(0.000)	(0.004)	(0.000)	(0.002)	(0.026)	(0.030)
Alpha	0.00063	-0.00027	0.00140	0.00183*	0.00177*	0.00096	0.00108	0.00055	-0.0004	-0.00067*	0.00130	0.00244*
	(0.216)	(0.365)	(0.219)	(0.071)	(0.090)	(0.197)	(0.376)	(0.641)	(0.365)	(0.093)	(0.292)	(0.077)
Adj. R^2	0.723	0.775	0.804	0.824	0.796	0.810	0.702	0.696	0.711	0.733	0.308	0.282

*, **, *** indicate significance at 10%, 5% and 1% levels based on two-tailed tests, p-values are robust and based on heteroscedasticity-consistent Huber-White adjusted standard errors.

Table 5: Continued

Panel B: Fund portfolios formed on CERTAINTY scores

	P1	*P2*	*P3*	*P4*	*P5*	*P6*	*P7*	*P8*	*P9*	*P10*	*Hedge1 returns*	*Hedge2 returns*
Rm-Rf	1.132***	0.911***	0.995***	1.208***	1.085***	0.877***	1.101***	1.106***	0.902***	0.930***	0.172***	0.115***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.002)
SMB	0.524***	0.409***	0.448***	0.516***	0.577***	0.529***	0.479***	0.401***	0.359***	0.388***	0.136***	0.189***
	(0.000)	(0.001)	(0.001)	(0.002)	(0.000)	(0.000)	(0.000)	(0.003)	(0.000)	(0.000)	(0.009)	(0.004)
HML	0.627***	0.582***	0.690***	0.619***	0.556***	0.550***	0.521***	0.583***	0.503***	0.484***	0.143***	0.072***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.006)	(0.006)
MOM	-0.178***	-0.219***	-0.235***	-0.274***	-0.270***	-0.282***	-0.233***	-0.209***	-0.190***	-0.191***	-0.079*	0.013**
	(0.000)	(0.002)	(0.007)	(0.000)	(0.005)	(0.000)	(0.003)	(0.003)	(0.000)	(0.001)	(0.088)	(0.045)
Alpha	0.00094	0.00025	-0.00040	0.00068	0.00105*	0.00209*	0.00101	0.00050	-0.00094	-0.00133	0.00227	0.00238
	(0.310)	(0.456)	(0.370)	(0.241)	(0.091)	(0.088)	(0.166)	(0.351)	(0.580)	(0.843)	(0.717)	(0.441)
Adj. R^2	0.813	0.805	0.790	0.786	0.704	0.756	0.698	0.760	0.810	0.803	0.366	0.295

*, **, *** indicate significance at 10%, 5% and 1% levels based on two-tailed tests, p-values are robust and based on heteroscedasticity-consistent Huber-White adjusted standard errors.

Table 5: Continued

Panel C: Fund portfolios formed on SELF-REFERENCE scores

	P1	*P2*	*P3*	*P4*	*P5*	*P6*	*P7*	*P8*	*P9*	*P10*	*Hedge1 returns*	*Hedge2 returns*
Rm-Rf	0.883***	0.917***	0.955***	0.990***	1.034***	1.007***	1.045***	1.015***	0.922***	0.874***	0.009***	0.160***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
SMB	0.338***	0.391***	0.407***	0.433***	0.412***	0.365***	0.369***	0.320***	0.375***	0.399***	-0.061***	0.013***
	(0.000)	(0.004)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.002)	(0.000)	(0.000)	(0.002)	(0.001)
HML	0.715***	0.692**	0.636***	0.680***	0.729***	0.762***	0.771***	0.677***	0.663***	0.601***	0.114**	0.128***
	(0.000)	(0.002)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.011)	(0.005)
MOM	-0.205***	-0.179***	-0.199***	-0.217***	-0.217***	-0.238***	-0.190***	-0.163***	-0.161***	-0.147***	-0.058***	-0.070**
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.008)	(0.035)
Alpha	-0.00018	0.00023	0.00085	0.00105	0.00139	0.00092	0.00092	0.00041	-0.00006	-0.00029	0.001	0.00168
	(0.312)	(0.455)	(0.479)	(0.570)	(0.432)	(0.308)	(0.515)	(0.722)	(0.532)	(0.538)	(0.292)	(0.566)
Adj. R^2	0.705	0.676	0.702	0.795	0.780	0.724	0.702	0.736	0.801	0.840	0.311	0.383

*, **, *** indicate significance at 10%, 5% and 1% levels based on two-tailed tests, p-values are robust and based on heteroscedasticity-consistent Huber-White adjusted standard errors.

The findings in Table 5 are interesting in a number of ways. Firstly, consistent with theoretical expectations, the regression coefficients for all the three Fama-French factors as well as the momentum factor are significant at the 1% level across all three panels. The positive coefficients in the case of Fama-French factors indicate that funds with investments in smaller, high beta, value-oriented stocks are associated with higher excess returns. We have also done this analysis without the momentum factor (i.e. the three factor model) and the adjusted R^2 slightly less than the corresponding figures for the Carhart model, which is consistent with theory.

Secondly, the results indicate that holding the portfolio with the highest OPTIMISM scores results in negative abnormal excess returns to the extent of around 1% per year (significant at the 10% level). The corresponding negative abnormal excess returns for CERTAINTY and SELF-REFRENCE are, respectively, around 1.6% and 0.4% per year. More broadly, P4, P5 and P10 alphas for OPTIMISM as well as P5 and P6 alphas for CERTAINTY are significant at the 10% level, while SELF-REFERENCE does not yield significant alphas in any of the portfolios. The observation that intermediate portfolios yield significant regression results is likely to be further evidence for the inverted-U relationship demonstrated in figure 3 below.

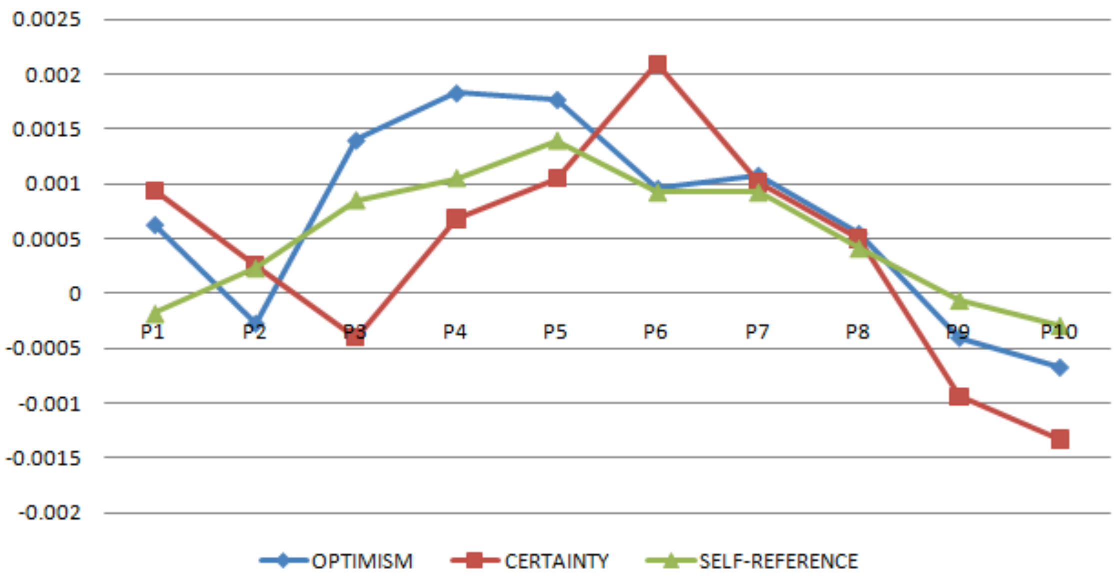

Figure 3: Average abnormal excess returns of ten equally weighted decile portfolios ranked by previous-year overconfidence proxies

P1 is the annually ranked portfolio of funds with the lowest overconfidence scores. P10 is the annually ranked portfolio of funds with the highest overconfidence scores.

Thirdly, in the case of OPTIMISM and CERTAINTY, the *Hedge2* strategy, on average, returns 2.9% based on shorting funds with extremely overconfident managers and going long in funds with normally (over)confident managers. The corresponding return in the case of SELF-REFRENCE is 2%. On the other hand, the *Hedge1* strategy, based on shorting funds with extremely overconfident fund managers and going long in funds with the least (over)confident fund managers, captures 1.6% based on OPTIMSIM scores, 2.8% based on CERTAINTY scores and 1.3% based on SELF-REFERENCE scores. In combination, the two strategies indicate the inverted U shape relationship between overconfidence and performance discussed earlier. This relationship can be best displayed by plotting the portfolio-specific Carhart alphas for each of the overconfidence proxies, as displayed in Figure 3 above.[9]

4.2. The Calendar Time approach

In this section, we employ the *calendar time portfolio approach* for analysing risk-adjusted investment performance.[10] In performing the calendar time analysis in the context of mutual funds, two steps are commonly taken. First, average excess return for the cross-section of funds is calculated. Second, a multifactor time-series regression model, such as the Fama-French or the Carhart model, is used to measure the risk-adjusted performance of the funds in a given timeframe. This approach allows robust statistical inference in the presence of cross-sectional dependence. In other words, by aggregating the returns of the sample funds into a number of portfolios, the problem of cross-sectional dependence amongst individual fund returns is eliminated (Hoechle, Schmid and Zimmerman, 2009).

For each fund-year observation during 2003-09, we calculate Carhart alpha using 36 monthly returns from month -24 to month 12 (month 0 being the publication month of the annual report).[11] Pooled cross-sectional time-series regressions are used to capture the effect of overconfidence on future investment returns using the following general equation:

$$E(R_{it}) - R_{ft} = \beta_0 + \beta_{1i}[E(R_{mt}) - R_{ft}] + \beta_{2i}E(\mathrm{SMB}_t) + \beta_{3i}E(\mathrm{HML}_t) + \beta_{4i}E(\mathrm{MOM}_t)$$

$$+ \beta_{5i}OPTIMISM_{it} + \beta_{6i}CERTAINTY_{it} + \beta_{7i}SELF\text{-}REFERENCE_{it}$$

where i indicates a particular fund and t refers to a particular month.

We perform the above regression four times, including each overconfidence proxy once individually in the model, and then including all three of them together as an overconfidence meta-variable. We use dummy variables to indicate that a fund belongs to the top 10% of each overconfidence proxy. For example, if fund *i* ranks in the top decile of optimism based on its 2006 annual report published in March of the same year, the dummy variables $OPTIMISM_{i200604}$ up to $OPTIMISM_{i200703}$ will be set to 1. Finally, we initially exclude year fixed effects from the model, and then add them to the model in order to compare the results.

Table 6 shows the results of the panel regressions for each of the overconfidence proxies with the reports categorized by sections. The optimism scores are based on the fund outlook

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[9] The magnitude of P1 regression coefficients slightly changes our supposed inverted-U relationship.

[10] The calendar time portfolio approach has many different applications in empirical finance, such as studying the performance of private investors, the long-run performance of stocks, and the performance analysis of investment funds, which is of interest in this study.

[11] We also replicate this approach using the prior 12-month returns, which yields similar results. However, the 36-month timeframe is preferable to mitigate noisy standard errors. We are grateful to Abhay Abhayankar for making this comment.

section, the self-reference scores are based on the past-performance discussion section and certainty scores are based on the whole narrative.

Table 6: The impact of overconfidence on subsequent mutual fund performance

(Reports analysed by section and grouped in deciles)

This table displays the results of panel regressions of fund returns during the **2003-09** period using the four Carhart factors (market excess return, SMB, HML, MOM) as well as fund-manager expressed optimism, certainty and self-reference dummy variables. The dummy variables indicate that the fund belongs to the top **decile** in each category (e.g. top 10% overoptimistic, etc.) The optimism scores are based on the fund outlook section, the self-reference scores are based on the past-performance discussion section and certainty scores are based on the whole narrative. Two-tailed t-statistics are reported in brackets.

Variable	Optimism	Certainty	Self-reference	*Overconfidence* Metavariable
Intercept	0.0061***	0.0191***	0.0094***	0.0094***
$R_M - R_F$	0.9442***	0.9729***	0.9417***	0.9506***
SMB	0.4263***	0.4388***	0.4112***	0.4378***
HML	0.4408***	0.4571***	0.4590***	0.4606***
MOM	-0.2015***	-0.2154***	-0.2110***	-0.2162***
Optimism	-0.5285** (-2.01)			
Certainty		0.1026* (1.65)		
Self-reference			-0.2742* (-1.82)	
Overconfidence Metavariable				-0.4109* (-1.77)

It can be inferred from the results in Table 6 that higher levels of net overconfidence (as proxied by optimism and self-reference) predict lower future monthly returns based on the Carhart model. Furthermore, optimism appears to be a more significant proxy for overconfidence based on the reported significance levels. The very low regression coefficient associated with certainty, however, bears a positive sign, contrary to expectation, which, we believe, may be due to the fact that fund managers commonly use a firm and resolute tone of voice in their reports to investors.

To what extent is the *accumulated* fund manager overconfidence in the past few years (and not only the past year) capable of explaining the effects observed above? To investigate this question, we substitute the prior one-year with the prior three-year OC scores in Table 7. Since SEC started filing mutual fund annual reports online in the Edgar database as of 2003, we have to start from 2006 to compute the average overconfidence scores. Another approach, not pursued here due to data collection limitations, is to take the average overconfidence scores of both annual and semi-annual reports, thereby increasing data points.

Table 7: The impact of overconfidence on subsequent mutual fund performance

(Reports analysed by section and grouped in deciles, average previous three-year proxies used)

This table displays the results of panel regressions of fund returns during the **2005-09** period using the four Carhart factors (market excess return, SMB, HML, MOM) as well as average **previous 3-year** fund-manager expressed optimism, certainty and self-reference dummy variables. The dummy variables indicate that the fund belongs to the top **decile** in each category (e.g. top 10% overoptimistic, etc.) The optimism scores are based on fund outlook section, the self-reference scores are based on the past-performance discussion section and certainty scores are based on the whole narrative. Two-tailed t-statistics are reported in brackets.

Variable	Optimism	Certainty	Self-reference	*Overconfidence* Metavariable
Intercept	0.0139***	0.0204***	0.0128***	0.0147***
$R_M - R_F$	0.7417***	0.7383***	0.7721***	0.8015***
SMB	0.5394***	0.5966***	0.5172***	0.5314***
HML	0.4033***	0.4129***	0.4304***	0.4228***
MOM	-0.3515***	-0.3752***	-0.3398***	-0.3429***
Optimism	-0.7144* (-1.92)			
Certainty		0.2250 (1.57)		
Self-reference			-0.3268* (-1.77)	
Overconfidence Metavariable				-0.5929* (-1.85)

The results still indicate a negative relationship between excess net overconfidence and future returns. However, they are relatively weaker compared to when previous one-year proxies are calculated, which may be due to the potentially transient nature of overconfidence among professional investors.

Next, we look at a broader picture by including quintiles rather than deciles in our analysis. In the results reported in Table 8, the dummy variables indicate belonging to the top quintile of the overconfidence proxy. The results are slightly weaker as one may expect, nevertheless still significant and suggestive of the inverse impact of net overconfidence of subsequent-year returns.

Table 8: The impact of overconfidence on subsequent mutual fund performance

(Reports analysed by section and grouped in quintiles)

This table displays the results of panel regressions of fund returns during the **2003-09** period using the four Carhart as well as fund-manager expressed optimism, certainty and self-reference dummy variables. The dummy variables indicate that the fund belongs to the top **quintile** in each category (e.g. top 20% overoptimistic, etc.) Two-tailed t-statistics are reported in brackets.

Variable	Optimism	Certainty	Self-reference	*Overconfidence* Metavariable
Intercept	0.0119***	0.0145***	0.0247***	0.0209***
$R_M - R_F$	0.8044***	0.9031***	0.8987***	0.8066***
SMB	0.3962***	0.4285***	0.4019***	0.3925***
HML	0.4804 ***	0.4116***	0.4622 ***	0.4790***
MOM	-0.3266***	-0.3005***	-0.3790***	-0.3559***
Optimism	-0.6515** (-1.97)			
Certainty		0.2730 (1.60)		
Self-reference			-0.4076* (-1.69)	
Overconfidence Metavariable				-0.6023* (-1.71)

An interesting question is how the observed negative impact of overconfidence on fund returns varies in the months following the publication of the annual report. If we regard the level of fund-manager expressed overconfidence as a snapshot taken at the time of producing the annual report, it is reasonable to expect that the impact of such overconfidence would be relatively stronger in the nearer months than the more distant future. We have investigated the 3-, 6-, and 9-month windows following the publication date of the annual report in Table 9.

Table 9: Short-term impact of abnormal overconfidence on subsequent mutual fund performance

This table displays the results of panel regressions of fund returns during the 2003-09 period using **3, 6, and 9** month timeframes following the publication of the annual report and the four Carhart factors as well as fund-manager expressed optimism, certainty and self-reference dummy variables. The dummy variables indicate that the fund belongs to the top decile in each category (e.g. top 10% overoptimistic, etc.) Two-tailed t-statistics are reported in brackets.

	9M	6M	3M
Optimism	-0.5348**	-0.5412**	-0.5661**
	(-2.05)	(-2.09)	(-2.14)
Certainty	0.1054*	0.1021*	0.1106*
	(1.67)	(1.71)	(1.78)
Self-reference	-0.2756*	-0.2812*	-0.3017**
	(-1.79)	(-1.88)	(-1.98)
Overconfidence	-0.4235*	-0.5027*	-0.4951**
metavariable	(-1.85)	(-1.92)	(-2.11)

The regression results reported in Table 9 seem to suggest that the impact of net overconfidence on future returns very slightly fades away in time. This is not surprising given the fact that most mutual funds publish, by definition, only one annual report per year, and thus investors have to refer to the most recent annual report in order to get a good picture of how a particular mutual fund is performing in general.

In order to test whether the way monthly returns are calculated affects the above regression results, we replicate the analysis using buy-and-hold returns instead of average monthly returns during the specified periods. However, we find that the regression results are not significantly different.

In a similar way, we test our model by including year fixed effects in the regressions. Year dummies can control for potential time-specific conditions that may have affected the funds' performance, such as boom and bust periods. However, the results are comparable and still suggest that abnormal levels of overconfidence can be detrimental to the fund's future investment performance.

Finally, we look at the relationship between the performance of mutual funds and their investment styles in the context of our research questions. To obtain a general perspective on the role of managerial overconfidence in this regard, we look at two broad categories of investment styles, namely, growth and value. This information is extracted from the funds' Lipper objective codes as reported in the CRSP database. Table 10 reports the regression coefficients for optimism, certainty and self-reference associated with each subgroup. The results suggest that highly overconfident growth-oriented fund managers are more negatively disadvantaged by this attribute in terms of subsequent returns, compared to their value-oriented peers.

Table 10: Investment style and the impact of overconfidence

This table displays the results of panel regressions of fund returns during in the 3 months following the publication of the annual report on the four Carhart factors as well as fund-manager expressed optimism. The optimism dummy variable indicates that the fund belongs to the top decile in its category. The funds are categorized by investment style (as per *Lipper Objective Code*). Two-tailed t-statistics are reported in brackets.

	Optimism Coefficient	Certainty Coefficient	Self-reference Coefficient	*Overconfidence* metavariable
Growth	-0.614**	0.1048*	-0.3304*	-0.4575*
	(-2.47)	(1.65)	(-1.80)	(-1.79)
Value	-0.429*	0.1100	-0.2025*	-0.4233
	(-1.89)	(1.51)	(-1.69)	(-1.59)

This finding is potentially interesting as it may suggest that growth-oriented fund managers have more incentive and opportunity to become overconfident by virtue of having to "believe" in and relate to the growth stories associated with their investments. However, a more detailed breakdown of fund investment styles and the associated impact of excess net optimism on future returns can be more useful. One may expect to find a similar general pattern suggesting that the effect of overconfidence on the future performance of a mutual fund depends, among other factors, on where the fund is located along the value-growth investment style continuum.

A question that may arise here is the link between this finding and the evidence of skill among growth-oriented fund managers. Chen, Jegadeesh and Wermers (2000) and Kosowski, Timmermann, Wermers and White (2006) have shown that growth-oriented funds possess better stock-selection skills than value-oriented funds. Can it be similarly posited that growth-oriented funds exhibit similar evidence of negative skill on the other side of the distribution, which may be due their susceptibility to certain behavioural biases such as overconfidence? This question, we believe, can provide fertile ground for future research in this area.

5. Conclusions, Implications and further research

In this paper, we set out to investigate the dynamic relationship between fund managers overconfidence and the performance of their funds. we ran Carhart four-factor regressions with overconfidence and year dummy variables with results suggesting that excess overconfidence does indeed diminish monthly returns following the publication of the annual report, assuming everything else is held constant. This effect is robust across different investment styles, although it is stronger among growth-oriented funds. Incorporating average scores for fund manager overconfidence over the previous three years results in similar regression coefficients, although relatively weaker.

The portfolio-tracking approach sheds further light on the dynamics of this effect. In general, there appears to be an inverted U relationship between overconfidence and subsequent investment performance. In particular, a hedging strategy based on shorting funds with extremely overconfident managers and going long in funds with normally (over)confident managers, on average, returns between 2.04% and 2.88% per year, depending on which overconfidence proxy is used to make fund portfolios. It was also observed that overoptimism and self-reference are likely to be more representative indicators of overconfidence than certainty, possibly due to the fact that fund managers write their reports in a resolute tone by normal practice.

5.1. Research implications

Our research results have a number of theoretical implications. Firstly, the results suggest that the predictive power of a multi-factorial asset pricing model such as Carhart's can be enhanced by adding independent risk factors proxying for investor psychology to the RHS of the model. To our knowledge, this is the first instance in the literature where fund manager psychology is quantified and accounted for in a traditional asset pricing model.

The finding of an inverted-U relationship between overconfidence and subsequent performance is consistent with the theoretical model proposed in Shefrin (2009) which illustrates the log-change of a measure corresponding to overconfidence bias. This finding also resonates with the relevant literature in other domains such as sport psychology.

In terms of practical implications, retail investors can benefit from the research results by starting to think more seriously about fund manager psychology when choosing their fund manager. Investing in mutual funds, as any other investment in financial markets, is inherently associated with significant uncertainty. Nevertheless, the research results of this study seem to suggest that retail investors are perhaps well advised to stay away from funds whose managers exhibit a high level of overconfidence in their annual reports.

Our findings can also have important implications for fund rating companies. Currently despite the power of fund ratings to influence asset flows in relation to mutual fund, there are doubts as to their actual relevance and usefulness (Amenc and Le Sourd, 2005). One aspect of the common fund rating methodologies that can be improved using the research findings of this thesis is the potential for incorporating certain fund-manager specific psychological attributes in the rating system. Initially, this need not replace existing ratings; rather it can help produce an alternative, more comprehensive fund rating methodology.

The investment industry as a whole, and fund trustees in particular, can also benefit by introducing some type of psychological screening in the fund manager selection process. The hiring of fund managers, in its traditional form, is heavily dependent on the manager's past performance record. A 2010 survey of US investment committees performed by a major investment house[12] lists the top five factors influencing the hiring decision as illustrated in Figure 4. The same survey reveals that the average length of fund manager retention in the industry is around 6 years (Figure 5).

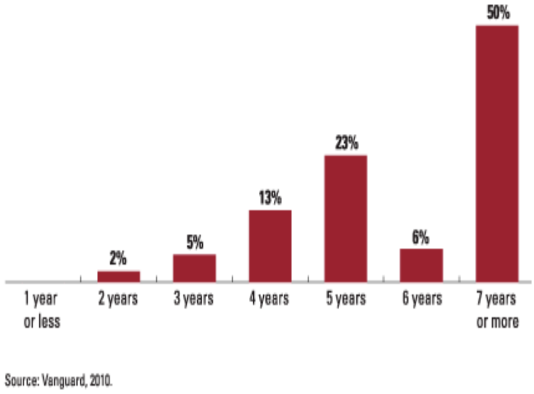

Figure 4: Top factors in hiring investment managers

Figure 5: Average length of relationship with investment managers

Hence, hiring and firing decisions are highly important in the mutual fund industry. We argue that by adding certain psychological attributes to the list of critical factors in hiring fund managers, investment companies can raise their chances of recruiting more "successful" managers. What is more, psychometric tests are already the norm in the recruitment process of most companies. Firms have been making increasing use of psychometric tests as part of the selection process for job vacancies. Psychometric tests attempt to measure the abilities, attributes, personality traits and various skills of the candidates under consideration for particular vacancies.

It is of course clear that fund managers do not operate in a context-free world. Holland (2006 & 2009) identifies a number of important intangibles in the work environment of fund managers. These include: "1) increasing significance of knowledge intensive processes, assets or intangibles in creating value within the enterprise, and within its immediate network of corporate alliances, suppliers, distributors, and customers. 2) increasing use of technology within these value creation processes. 3) major changes in the corporate value creation process such that knowledge creation, articulation, processing and leveraging, has become a central survival activity for multinational companies. 4) changes in corporate structure from top heavy, multi layered managerial hierarchies to flat hierarchies, and to companies establishing alliance and networks with companies in the same industry and with suppliers and distributors. 5) increased internationalisation or globalisation of companies and industries. 6) radical changes in corporate strategy arising from the above forces."

The above forces can potentially influence fund manager behaviour in direct or indirect ways. For example, in the case of disclosure behaviour, flat managerial structures may lead to corporate preference for secrecy over private disclosure. Equally, they can also lead to

[12] Vanguard Institutional Investors, the summary of survey results can be found at: https://institutional.vanguard.com/VGApp/iip/site/institutional/researchcommentary/article?File=NewsHireFire

preference for private disclosure over voluntary public disclosure (Holland, 2006). In other words, fund managers may be motivated to exercise some level of self-censorship in communicating to their investors through fund manager reports. They may do so in an attempt to safeguard the larger interests of the financial institution in which they work. Clearly, the degree to which fund managers may be influenced by such organisational pressures is very difficult, if not impossible, to measure. However, it is important to recognize these intangible factors as the limitations of a largely context-free analysis.

5.2. Further Research

A potentially rich area for further research in the context of this paper is the mutual link between overconfidence, fund flows and performance. In the conceptual model used in this study, the simplifying assumption was made that abnormal overconfidence affects the quality of investment decisions, and by extension investment returns, through three intermediate variables grounded in psychology (anxiety, concentration and motivation). However, a more complicated picture emerges when one considers the fact that superior past performance is often associated with increased fund inflows, and inferior past performance is often associated with increased fund outflows. In other words, one may expect fund inflows and outflows to be another set of intermediate variables through which the performance of an overconfident fund manager may suffer.

The issue of performance persistence in the negative domain also provides fertile ground for future research. While the evidence is mixed with regards to persistence of performance, the bulk of prior research appears to agree that genuine stock selection skill exists only among a very small number of fund managers, if at all. However, persistence of performance in the negative domain is more strongly observed, with some studies suggesting that inferior fund managers are not merely unlucky; rather they demonstrate “bad skill” (e.g. Cuthbertson, Nitzsche and O'Sullivan (2008), using 1975-2002 mutual fund data). One might naturally ask: “Could abnormal overconfidence be a component of this bad skill?” Whether bad skill is due to lack of relevant experience and knowledge, susceptibility to certain behavioural biases such as overconfidence, other factors or even predominantly down to luck, is clearly a very researchable area.

Further research can also include an additional set of control variables on the RHS of the asset pricing model. Glaser and Weber (2010) list a number of factors that are generally considered to have an influence on the actual level of individual overconfidence. These factors include, among others, gender, culture, availability of relevant information, monetary incentives and individual expertise.

Another possible area for further investigation is the effect of overconfidence on compensation contracts and vice versa. Gervais, Heaton and Odean (2011) argue that overconfidence has different effects on managers depending on their risk appetite. For example, since a risk-averse manager’s overconfidence makes him less conservative, it is easier and cheaper to encourage him to pursue valuable risky projects. Interestingly, “when compensation endogenously adjusts to reflect outside opportunities, moderate levels of overconfidence lead firms to offer the manager flatter compensation contracts that make him better off. Overconfident managers are also more attractive to firms than their rational counterparts because overconfidence commits them to exert effort to learn about projects.” While the authors present a model where overconfidence can increase value by aligning incentives and mitigating moral hazard, they also conclude that too much overconfidence has a negative effect since it leads managers to accept highly convex compensation contracts that expose them to excessive risk. Given the complexity of the factors associated with fund performance, it needs to be recognized that fund manager overconfidence is only one part of the overall story.

Further research can address a number of limitations in the data collection process. For example, a number of mutual funds with annual reports not easily accessible in electronic format were deleted from the sample. These funds can be added back into the sample through further retrieval attempts. In addition, to increase the sample size and inter-observation frequency, future researchers can collect and analyse semi-annual reports in addition to annual reports. Doing so will reduce the duration between overconfidence observations to six months. However, the downside of this approach is that semi-annual reports do not always have the same richness of narrative information as annual reports.

Finally, further work can explore a number of avenues related to the current study. Detailed breakdowns on fund sectors or fund families can potentially reveal interesting results. Additionally, one can explore a similar set of mutual funds based in a different location (e.g. UK) to look for possible cross-cultural differences in the propensity for overconfidence. Assuming the availability of disclosure data, hedge funds can also prove a rich area for studying fund manager overconfidence. This is because the nature of investing in hedge funds and the distinct features of hedge funds as investment vehicles may drive hedge fund managers to become more emotionally associated with their investments, and thus overconfidence can assume a more pronounced role in professional investment decisions.

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