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**PROFESSIONAL INVESTOR PSYCHOLOGY AND
INVESTMENT PERFORMANCE: EVIDENCE FROM
MUTUAL FUNDS**

Arman Eshraghi

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ABSTRACT

In the seven decades following the Investment Company Act of 1940 coming into force in the United States, the mutual fund industry has undergone dramatic changes including, some argue, a transition from stewardship to salesmanship with asset-gathering becoming the industry's driving force. As fund managers incrementally assumed a more pronounced role in the investment fund industry, an emerging strand of finance literature focused on their characteristics and their potential impact on investment performance. While a large body of academic research concurs that fund managers cannot outperform systematically better than chance, there are also a significant number of studies that link the psychological characteristics of investors to their investment performance. Importantly, we know that fund managers, as a representative sample of professional investors, often have to operate under enormous anxiety and associated psychic pressures. In their effort to cope with these pressures and make sense of an immensely unpredictable and complex work environment, a wide range of psychic defences and behavioural biases may be triggered.

The purpose of this research is to investigate, on the one hand, to what extent mutual fund managers are prone to overconfidence and associated behavioural biases such as self-serving attribution. On the other hand, the extent to which overconfidence, proxied by a wide range of variables including overoptimism, excessive certainty and excessive self-reference, may have any bearing on fund performance is of interest. The fundamental question is why, how, and through which mechanisms does overconfidence affect performance. The underlying research questions are motivated by three large areas of research: studies of mutual fund performance and persistence, studies of financial accounting narratives, and studies of professional investor psychology. I also explore how overconfidence is fundamentally generated and, in a sense, resorted to by fund managers as a defence mechanism against the psychic pressures of having to work in a highly intangible, complex and uncertain environment. Drawing on evidence from fund manager reports written for investors, I explain how they use the medium of narratives, and in particular stories, to make sense of what they do as fund managers and their added value for clients. I demonstrate how analysing fund manager commentaries, both through computer-assisted corpus-linguistic approaches and through the "close reading" method, sheds light on the link between fund manager psychology and investment performance. In particular, from the perspective of narrative analysis, I explain how fund managers write their reports in distinguishably different genres depending, among others, on their past performance record, fund size and investment style. In addition, I establish in a longitudinal study that the overall economic environment in which fund managers operate does influence the rhetoric of fund manager reports as well as the evidence for the Pollyanna hypothesis.

My findings also suggest that excessive overconfidence is associated, to a large extent, with diminished future investment returns. While superior past returns are expected to increase fund manager confidence which, in turn, may introduce the overconfidence bias in the investment decision-making process and thus diminish returns (through inefficient stock selection, suboptimal market timing and other possible mechanisms), this is not a simple regression towards the mean. The asset pricing model employed in my empirical analysis, the Carhart four-factor model, controls for the effect of previous-year momentum, and my overconfidence measures are only slightly correlated with the momentum figures. Hence, one is led to the conclusion that the narrative-based variables used in this study indeed capture some aspect of the professional investor psychology, and are capable of enhancing the explanatory power of conventional asset-pricing models such as Carhart's.

In investigating the dynamic relationship between fund manager overconfidence and investment performance, the cross-sectional variations in my study demonstrate that superior past performance boosts overconfidence as measured by all proxies employed. In addition, 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, yields positive average returns. The impact of overconfidence on subsequent returns is robust across different investment styles, although it is stronger among growth-oriented funds. Incorporating average scores for fund manager overconfidence over longer periods yields similar results. In addition, fund manager duration appears to correlate with managerial overconfidence in the long term.

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DECLARATION

I certify that this thesis does not incorporate any material previously submitted for a degree or diploma in any University; and that to the best of my knowledge and belief it does not contain any material previously published or written by another person where due reference is not made in the text. I also certify that the thesis has been composed by myself and that all the work is my own.

Arman Eshraghi, December 2011

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CHAPTER 1 - INTRODUCTION

The investor's chief problem - and even his worst enemy - is likely to be himself... Individuals who cannot master their emotions are ill-suited to profit from the investment process.

- Benjamin Graham (1973), “The Intelligent Investor”, p. 283.

Professional investment may be likened to those newspaper competitions in which the competitors have to pick out the six prettiest faces from a hundred photographs, the prize being awarded to the competitor whose choice most nearly corresponds to the average preferences of the competitors as a whole; so that each competitor has to pick, not the faces which he himself finds the prettiest, but those which he thinks likeliest to catch the fancy of the other competitors, all of whom are looking at the problem from the same point of view.

- John Keynes (1936), “The General Theory of Employment, Interest and Money”, p. 156.

1.1 OVERVIEW

The purpose of this chapter is to introduce the thesis and set the scene for the following chapters. I discuss the background and objectives of the research, and justify why it is important to study investor psychology in general. In the broad context of behavioural finance and investor psychology, I frame my research questions and explain the approach used to investigate them, before providing a summary of the research results and the original contribution to the relevant literature. I then conclude with an outline of the thesis structure and a brief summary of the following chapters.

1.2 BACKGROUND

Traditional finance uses theoretical models which predominantly assume that 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. As Barberis and Thaler (2003) remark, “unfortunately, after years of effort, it has become clear that basic facts about the aggregate stock market, the cross-section of average returns, and individual trading behaviour are not easily understood in this framework.”

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 (2008), among others, provides a detailed survey of studies linking investor psychology to asset pricing and claims 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. Based on the behavioural finance literature, overconfidence clearly belongs to this list. As Plous (1993) argues, “no problem in judgment and decision making is more prevalent and more potentially catastrophic than overconfidence.”

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.

To properly understand overconfidence, an excellent approach is 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. Our early ancestors who lived in the very hostile environment of African savannahs and had to step out of their caves to hunt for food in competition with the wildest predators of that age, did in fact require optimism, and perhaps even some level of overconfidence to take this first step.

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 I 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)).

This study focuses on professional investors. 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.

I 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 thesis explains, may affect investment performance in several ways.

1.3 RESEARCH QUESTIONS

The phenomenon of overconfidence, 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. I have found 1,517 peer-reviewed journal articles published between 2000 and 2010 in a major literature database that contain the keyword "overconfidence".²

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 research, 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

² The search was conducted in January 2011 on the database Business Source Premier (*EBSCO Host*). Almost half of the total number of articles (724 items) are published after 2007, clearly showing a rising trend. A search in the *ScienceDirect* database yielded similar results.

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 thesis:

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. How does the self-attribution bias interact with overconfidence and investment performance?
4. How does self-attribution bias driving overconfidence manifest itself in the way fund managers communicate their investment results to their clients, in particular by engaging in "storytelling"?
5. How does the above process relate to the anxieties generated by having to explain, justify and cope with poor past performance as well as a highly uncertain working environment?
6. Can what we know about fund manager overconfidence help investment companies recruit more "successful" managers?

1.4 THE OBJECTIVES OF THE RESEARCH

My research aims to achieve a number of objectives. *Firstly*, I set out to explore the extent to which mutual fund managers are categorically prone to overconfidence. It has to be noted that overconfidence is a bland term and can have several meanings in different contexts. I clearly specify what I mean by overconfidence in each case and make use of a number of different proxies associated with measuring this construct including overoptimism, excessive certainty, self-reference and tone.

Secondly, I investigate whether a fund manager's overconfidence can affect her investment performance in any significant way. I survey the literature to arrive at some theoretical expectations in this context and empirically test several hypotheses. The research results can potentially be informative to the fund manager skill versus luck debate as well as the ongoing debate on performance persistence.

Thirdly, this study demonstrates how the self-serving attribution bias interacts with investment performance and overconfidence. It also shows how fund managers use the medium of narratives, and "stories" in particular, to generate conviction in what they are doing, and to be able to continue their highly complex and demanding task of adding value for their clients despite having to invest in an environment with uncertain and almost unforeseeable outcomes. Through narrative analysis, I illustrate how fund managers who are swamped by an enormous amount of conflicting information that needs to be processed and made sense of in some way, can find only a loose connection, at best, between their investment thesis and successful outcomes. *Finally*, I explore the implications of the research results for fund manager selection, and overall financial regulation of the mutual fund industry.

1.5 THE ORIGINALITY OF THE RESEARCH

This research is located within the mainstream of behavioural finance and formal narrative (content) analysis in accounting and finance. It lies at the interface of the literature that seeks to measure whether mutual fund manager skill exists, the literature on the psychology of professional investors and the recent research in the domain of emotional finance which explores how fund managers deal with and make sense of their inability to do what they are expected to do, which is to outperform the market on a measurable basis knowing on one level this is beyond their control.

In addition, the thesis builds on the literature on content analysis of corporate narratives e.g. investigating Chairmen's Statements, etc. The research results make original contributions to the understanding of how certain behavioural and emotional mechanisms are employed by professional investors to operate in a very uncertain environment, and how they possibly influence future fund performance.

Furthermore, the current study is, to the best of the researcher's knowledge, one of only two studies that have examined the issue of overconfidence among mutual fund managers in detail (the other study being the Choi and Lou (2008) working paper). In addition, the approach used to measure overconfidence, as will be explained in the subsequent sections, is highly original and makes use of a large sample of fund annual reports.

1.6 THE CHOICE OF TOPIC AND RESEARCH DESIGN

A robust research design clearly requires an appropriate *choice of research topic*. I have chosen the topic of “professional investor psychology and investment performance” for a number of reasons. Importantly, the broad area of behavioural finance and the sub-domain of emotional finance is an emerging and increasingly influential area of finance research with significant implications in the finance industry. In addition, the above topic is well suited to both qualitative and quantitative research methods, and I have used both methodologies to enhance the robustness of this study. Finally, my epistemological perspective, interpretivism, is in accordance with the framework of this research. Interpretivism, as explained by Bryman (2004), “requires the social scientist to grasp the subjective meaning of social action”, and holds that meaning is imposed on objects by subjects. In this research, the former can be seen as investments in general, and the latter can be construed as fund managers under study.

My research is based on a combination of *longitudinal design* and some *case studies*. The longitudinal design which constitutes the major part of my research studies the impact of overconfidence on a large sample of fund managers using regression analysis. The case studies intend to investigate a number of fund manager narratives that are considered theoretically-contributing cases in terms of how they make investments in the presence of emotions. Hence, from a methodological perspective, the research design falls into the *flexible design* category as it seeks to explain the role of dynamic variables in a constantly-changing context. Accordingly, the research strategy used seeks to generate a theory explaining the role of

overconfidence in investment decision-making. This conforms to interpretivism as my epistemological position.

The longitudinal design is chosen over other possible designs since longitudinal research is best suited for studying changing social processes, as Blaikie (2000) explains. In addition, other possible designs do not sit well with the requirements of my research. For instance, a cross-sectional design is not suitable for my purpose because the process I am looking at is dynamic and constantly changing. That is to say, the performance of a fund manager cannot be judged by measuring her performance at a single point in time. An experimental design approach is also not appropriate, since it is very difficult, for obvious reasons, to gather a sufficiently large sample of fund managers at the same place and time for conducting a realistic experiment.

This thesis 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.

Mixed methods research is not uniquely defined in the literature. Johnson et al. (2007) reviews 19 studies to demonstrate the significant variation in the definition of this concept. Most studies in this area concur that mixed methods research should include both a quantitative and qualitative component. However, with regards to variations in definitions, Grafton et al. (2011) write: “Where inconsistencies and disagreements seem to originate is in the consideration of how these quantitative and qualitative components are related, and whether these components reflect quantitative and qualitative data collection and analysis techniques (i.e. methods) and/or quantitative and qualitative approaches to research (i.e. methodologies).”

Grafton et al. (2011) also argue that further points of contention exist in the emphasis placed on the quantitative and qualitative elements of the study, the stages of the study at which quantitative and qualitative components are combined, and the order

in which quantitative and qualitative methods are used. Hence, the mixed methods research is not a clearly defined methodology.

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). Triangulation can refer to *within-methods* triangulation (i.e. the use of several quantitative or qualitative components) as well as *between-methods* (the use of both quantitative and qualitative components). With the above introduction, this thesis mainly seeks to adopt a between-methods approach although each of the qualitative and quantitative sections consist of several elements.

1.7 THE RESEARCH METHODOLOGY: OVERVIEW OF DATA COLLECTION AND ANALYSIS

This section provides a brief overview of the methodological aspects of the current study. I take several steps to arrive at the reported results. Firstly, US mutual fund annual reports belonging to the 2003-2009 period are extracted from the EDGAR database provided by SEC. The year 2003 is chosen since it is the first year in which SEC required investment companies to file annual reports as mandatory disclosures.

Secondly, the procedure of *content analysis* is used to analyse the linguistic features of fund manager narratives. Content analysis is based on the assumption that the language people choose to express themselves in contains information about the nature of their psychological states, an assumption implying a presentational or descriptive model of language as explained in Viney (1983). In order to analyse the fund manager narratives, I mostly use the *Diction* computer program. I use three proxies to measure overconfidence given the considerable body of textual data available, and employ *Diction* to extract these variables. *Diction* is a well-known content analysis software that is widely used in the field of finance and accounting, among other domains, to produce consistent narrative-based scores for any given

text.³ It has been used extensively to analyse political speeches, CEO 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 praise, satisfaction, or denial. In this study, I predominantly use the optimism and certainty master variables used in *Diction*. I also make use of *Concordance* to complement *Diction* results in some sections.

Thirdly, I use the *Carhart four-factor model* to test an augmented model using regression analysis. Generally, momentum strategies that recommend buying stocks with high returns and selling stocks with low returns over the previous 3 to 12 months generate significant excess returns in most equity markets. Carhart (1997) famously constructs a risk factor to capture this one-year momentum anomaly, and proposes a four-factor model by adding the momentum risk factor to the Fama French three-factor model, which already controls for the effect of excess market returns, size and book-to-market value. Carhart demonstrates that, compared to the Fama French three-factor model, his model significantly decreases the average pricing errors of portfolios that are sorted by one-year lagged returns. In my study, the overconfidence scores and other related variables derived from the narratives are incorporated in the original Carhart four-factor model as additional independent variables. The mutual fund monthly returns, sourced from the CRSP Mutual Fund Survivor-bias Free Database, are then regressed on the four factors as well as the narrative scores that represent fund manager overconfidence.

1.8 THE OVERALL CONCLUSIONS

The empirical results suggest, among others, that excessive overconfidence is associated with diminished future investment returns. I develop a theoretical model that seeks to explain why, and through which mechanisms, overconfidence affects decision-making and hence, investment performance. From a psychological viewpoint, the effect of overconfidence on judgement and decision-making can be

³ A list of academic studies that have used the *Diction* software can be found at www.dictionsoftware.com

explained by the dynamics between overconfidence and three important intermediate variables i.e. anxiety, concentration and motivation. As I will explain in detail, the bulk of research evidence in cognitive psychology suggests that while higher confidence levels are associated with lower decision-making anxiety, they are also associated with lower task-specific concentration and lower general motivation. Overall, this results in an inverse relationship between overconfidence and decision performance, in the form of an inverted-U shape.

From a pure finance perspective, the observation that superior past returns can introduce the overconfidence bias in the investment decision-making process of fund managers, and thus result in diminished returns (possibly through inefficient stock selection, suboptimal market timing etc.) may initially be interpreted as a type of regression towards the mean. However, the Carhart four-factor model used in this study, by definition, already controls for the effect of previous-year momentum, and the overconfidence measures in my study are only slightly correlated with the momentum figures. Hence, one is led to the conclusion that the narrative variables indeed capture some aspect of the fund manager psychology that can enhance the explanatory power of a conventional asset-pricing model such as Carhart's.

The impact of overconfidence on subsequent returns is robust across different investment styles, and is generally stronger among growth-oriented funds. As a possible explanation, I argue that the nature of investing in growth stocks lends itself more easily to fund managers becoming overconfident. In other words, growth-oriented fund managers often appear to believe in an underlying "growth story" associated with the stocks they invest in, and as I illustrate in Chapter 5, they seek to communicate these stories in a style which is often more pronouncedly dramatic and emotional compared to that used by value-oriented managers.

I arrive at similar conclusions by incorporating average scores for fund manager overconfidence over longer periods. I also demonstrate that overoptimism and self-reference are more representative proxies of overconfidence than certainty, possibly due to the fact that professional investment writers are resolute by normal practice. Finally, fund manager duration appears to correlate with fund manager expressed overconfidence in the long term. For the same cohort of fund managers studied

throughout the range of the sample data, measured overconfidence tends to rise steadily and in agreement with theoretical expectations.

In another section of the thesis, I explain how overconfidence is generated and, in a sense, resorted to by the fund manager as a defence mechanism against the psychic pressures of having to work in a highly competitive, complex and uncertain environment. Drawing on suggestive evidence from fund manager's commentaries written to shareholders, I explain how they use the medium of narratives, and in particular stories, to make sense of what they do as fund managers and their added value for clients. I also explain how analysing fund manager commentaries, both through computer-assisted corpus-linguistic approaches and through the "close reading" method, sheds light on the link between fund manager psychology and investment performance. What can be generally learnt, from the perspective of genre analysis and corpus linguistics, is that fund managers write their reports in distinguishably different genres depending, among others, on their past performance record, their size and their investment style. My hypothesis regarding the existence of distinct rhetorical genres in fund manager reports is supported using a number of cross-sectional tests.

In addition, I establish in a longitudinal study that the overall economic environment in which fund managers operate does influence the rhetoric of fund manager reports in aggregate. I also test the *Pollyanna* hypothesis⁴ for which my results provide support particularly among a number of categories such as loss-making funds. For instance, the keywords "market" and "economy" are more frequently used among funds with negative absolute returns, and the least profitable funds in the positive return category. These observations seem to suggest that fund managers, in aggregate, refer to the market and the economy as external performance detractors in a self-serving way, which is consistent with the anecdotal evidence based on close-

⁴ The *Pollyanna* hypothesis (or principle) describes the tendency people have to agree with positive statements describing them. The word *Pollyanna* refers to the heroine of a 1913 novel of the same name by Eleanor Porter, an American writer, in which she portrays a person characterized by irrepressible optimism and a tendency to find good in everything. This character type is, in fact, the exact opposite of *Cassandra* who, in Greek mythology, is a prophetess whose predictions were always true but never believed by others.

reading the fund annual reports. The frequency of use for the keyword “index” suggests a similar conclusion, i.e. fund managers tend to make benchmark comparisons more frequently when performance is in the negative domain, and in doing so they strategically shift the reader’s attention away from the fact that he has, in fact, lost money by investing in the fund.

To a certain extent, one may be able to conclude that fund managers strategically adjust the overall tone and rhetoric of their reports in a self-serving way. However, it is equally plausible for this behaviour to stem from the unconscious psychological processes that may be in play in the minds of fund managers, since, as it is demonstrated throughout this study, the underlying investment story can be an excellent sense-making implement for professional investors in general.

1.9 THE STRUCTURE OF THE THESIS

This thesis comprises eight chapters, with chapters 5, 6 and 7 comprising my empirical results. **Chapter 1**, this chapter, has introduced the background to the research in addition to the research questions and the area of focus in the thesis. The research objectives, a brief overview of the research approach as well as a summary of the conclusions are also discussed.

Chapter 2 presents the review of literature on the role of overconfidence in investment performance of professional investors. The evidence on measuring the performance of mutual funds is anchored in the traditional finance literature, and presented in this chapter in relation to the research questions in the thesis. In reviewing a second strand of literature, the studies on overconfidence, which are grounded in psychology and, *inter alia*, linked to recent developments in behavioural finance research, are discussed. The third strand of literature, inextricably linked to my research questions, is the research on corporate annual reports and managerial obfuscation as well as impression management incentives. Finally, I identify the gaps in the literature and prepare the conceptual framework for the research questions.

Chapter 3 presents my hypotheses and the variables used to test them. I present null hypotheses for the potential impact of several psychological attributes (proxying for overconfidence) on the subsequent performance of investment decisions made by fund managers. Further null hypotheses test for the correlation of these attributes with past performance as well as the dynamic change of these measures alongside increase in fund manager duration. In addition, I discuss, in detail, the methodological approach employed in the thesis.

Chapter 4 explains my sample selection process, details of the data and relevant descriptive statistics. The first part of the chapter presents information on the sources of the data used in the thesis including the EDGAR database as well as the CRSP Mutual Fund Database. The second part presents the sample selection criteria, and data reduction considerations before providing preliminary descriptives.

Chapter 5 examines how the self-attribution bias drives overconfidence through analysing fund manager commentaries using “close reading” methodology. By manually coding a random sample of fund manager reports in the spirit of Jameson (2000), I identify different “story types” embedded in fund manager narratives and explain how self-attribution bias and overconfidence is manifest in them. Further, I establish connections among these stories and the funds’ past investment performance, and use the results to explain the sense-making process of professional investors in their very unique work environment.

Chapter 6 empirically investigates how past investment results influence fund manager tone and report readability which are closely associated with fund manager overconfidence. I focus on the way fund managers set out to communicate financial performance to their clients. By studying the corpus-linguistic features of fund manager reports, I demonstrate how different groups of fund managers develop the core message in their narratives in very different way (i.e. genres) in light of prior performance. In addition, this chapter also explores how past performance affects overconfidence directly as measured by the three proxies of overoptimism, excessive certainty and excessive self-reference.

Chapter 7 empirically investigates the impact of fund manager overconfidence on future investment returns. I use the well-known Carhart four factor asset pricing model as the basis of an empirical model which I seek to improve by adding independent variables proxying for fund manager psychology. I test the research hypotheses using a number of different approaches including the calendar-time method and the portfolio-tracking method. The chapter includes controls for other potential confounding factors, and tests for overall robustness of the empirical model.

Chapter 8 presents a summary of the findings and draws conclusions relevant to the proposed research questions. The implications of the research both for theory and practice are discussed in detail. In addition, the research limitations are explained and several suggestions for areas of future research are provided.

CHAPTER 2 - LITERATURE REVIEW

2.1 INTRODUCTION

This chapter presents a summary of prior research related to the current study and identifies a number of research gaps which serve to motivate the research questions briefly introduced in chapter 1. With this objective, several strands of literature are examined in the context of the current research. I review some research evidence on mutual fund investment performance and persistence, and the overconfidence effect and associated psychological concepts, in order to investigate the first three research questions in the thesis:

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. How does the self-attribution bias interact with overconfidence and investment performance?

Then, I review some studies on the structure of narrative disclosure in annual reports in order to answer the remaining research questions:

4. How does self-attribution bias driving overconfidence manifest itself in the way fund managers communicate their investment results to their clients, in particular by engaging in "storytelling"?
5. How does the above process relate to the anxieties generated by having to explain, justify and cope with poor past performance as well as a highly uncertain working environment?

The chapter is organised as follows: Sections 2.2 and 2.3 introduce key studies on mutual fund performance and persistence. Section 2.4 seeks to review the literature

on the overconfidence effect, and introduces the key relevant studies mostly from the area of psychology. Section 2.5 discusses the impact of overconfidence in the field of finance, while section 2.6 examines the parallel links between overconfidence and performance in other domains. Finally, section 2.7 develops a conceptual model that drives the thesis and inspires the research questions.

2.2 HOW IS THE INVESTMENT PERFORMANCE OF MUTUAL FUNDS MEASURED?

This thesis focuses on US mutual funds. The US mutual fund industry has witnessed dramatic changes in the seven decades following the Investment Company Act of 1940 coming into force. Bogle (2005) explains that the industry transformed tremendously from being organized, operated, and managed in the interests of fund shareholders to one that mostly serves the interests of managers and distributors. With this transition from stewardship to salesmanship, asset-gathering became the industry's driving force. As fund managers incrementally assumed a more pronounced role in the mutual fund industry, a new strand of mutual fund literature increasingly focused on their characteristics and their potential influence on performance.

So far, despite the near five-decade attempt to reach a consensus, there is no agreement in the academic literature with regards to the most appropriate benchmarks and models for performance measurement. Since measurement of investment performance is a key part of my thesis, I briefly introduce the most relevant and influential papers in this area and point out the existing research gaps. Then, I locate my thesis in the literature and discuss its potential contributions.

In order to empirically examine the link between mutual fund performance and fund manager psychology, first it is necessary to measure investment performance. Since the early 1960's, more than five decades of academic studies have been dedicated to mutual funds in areas as diverse as performance measurement, career concerns of fund managers, fund characteristics, marketing and advertising of mutual funds, fund managers and behavioural biases, etc. In the vast body of mutual fund literature that

has formed during this period, the topic of performance measurement and the closely related areas of performance persistence and the skill versus luck debate have been subject to considerable academic and industry attention. This is of course not surprising given that most individuals invest in mutual funds in the expectation of making profits, and the performance of mutual funds and their managers has to be evaluated in order to provide an appropriate basis for future investment decisions. However, there are two challenging issues in measuring fund performance that make this task considerably difficult: (1) the choice of an appropriate benchmark, and (2) the choice of the best model for measuring performance.

The academic literature on mutual funds relevant to the current study starts with Close (1952), perhaps the first academic paper on this subject, which discusses the differences between closed-end and open-end funds and anticipates many future contributions to this literature. The different criteria required for assessing performance of different types of funds is explained by Brown and Vickers (1963) who demonstrate that funds on average perform no better or worse than the markets they operate in. Sharpe (1966) is among the first studies to use concepts from modern portfolio theory, and builds on his earlier development of the CAPM in Sharpe (1964). He explains that an optimal investment portfolio is the one with the greatest reward-to-variability ratio or *Sharpe* ratio. Sharpe uses data from 34 open-end mutual funds from the period of 1954-1963, and finds significant variability in their Sharpe ratios, with 0.78 for the best and 0.43 for the worst performing funds in his sample. He attributes this considerable variation to either excessive fund expenditure or possible fund manager investment skill. Sharpe also finds some evidence of persistence in the fund rankings.

Do fund managers have any actual ability to anticipate major turns in the stock market? Treynor and Mazury (1966) ask this question in their study: "Is the fund manager speculating if he attempts to anticipate major market movements? Or is he negligent if he fails to try?" Examining a sample of 57 open-end mutual funds from 1953 to 1962, they compute a characteristic line for each mutual fund based on its volatility in both good and poor market years. Since they discover no curvature in any of the characteristic lines, they conclude that none of the fund managers has the

ability to outguess the market and hence should not be held accountable for failing to predict changes in market direction.

Jensen (1968) is one of the first examples of measuring absolute performance. His data covers 115 mutual funds spanning 1945-64, and the S&P 500 returns are used as a market proxy. He shows that the funds on average earned 1.1% less than they should have earned given their level of systematic risk. By evaluating the statistical significance of alphas (or risk-adjusted returns), Jensen finds little evidence that any given fund does better than pure chance. Jensen's alpha is now commonly used to measure the relative performance of equity mutual funds.

Carlson (1970) shows that mutual fund performance with respect to the market is affected by fund type, time period under study, and the choice of benchmark. He argues that mutual funds need to be grouped by broad investment objectives before their performance can be compared in any way. Studying funds from the period 1948-1967, the author finds that past performance has little predictive value for future performance.

Subsequently, with the development of more advanced theories of market equilibrium, researchers make further attempts to deconstruct mutual fund performance. Fama (1972), for example, finds that mutual fund returns can be generated by two distinct activities: stock selection and market timing. Kon and Jen (1979) employ the Sharpe-Lintner-Mossine and Black models of market equilibrium to study the market timing and stock selection performance of mutual funds. They conclude that fund managers, both individually and on average are unable to recover their research expenses, fees and other costs through superior stock selection.

Kon (1983) focuses on the market-timing performance of mutual funds and shows that fund managers who believe they have above average market timing ability, adjust the risk level of their portfolios in advance of market movements. Thus he correlates evidence of systematic risk non-stationarity for a fund with its timing activity. Examining a sample of 37 mutual funds from 1960 to 1976, Kon finds that a number of funds display significant timing ability/performance, but in aggregate, fund managers have little or no information ahead of market movements. Using a

different methodology that involves partitioning the return data into up-market and down-market periods and examining them separately, Chang and Lewellen (1984) similarly find no overall evidence of skilful stock selection or market timing ability by mutual fund managers.

The study by Grinblatt and Titman (1989) is another comprehensive examination of mutual fund performance. They investigate both actual returns and gross portfolio returns, which differentiates their work from previous studies. Using quarterly data for the 1975-64 period, they test for abnormal returns while controlling for survivorship bias. Although the authors do not reject the likelihood of superior performance among growth funds, aggressive growth funds, and smaller funds, they show that these funds have the highest expenses, hence eliminating any likelihood of abnormal investor returns.

In a study using the same sample of funds from their 1989 article, Grinblatt and Titman (1993) introduce a new measure of performance, the “Portfolio Change Measure”. This new measure does not suffer from survivorship bias and benchmark problems earlier pointed out by Roll (1978) and others. They find that aggressive funds exhibit the strongest evidence of abnormal performance, and that their performance persists both for superior and inferior funds. However, as prior research suggests, any abnormal investment returns are eliminated by fund expenses and transaction costs. Nevertheless, investors may be able to achieve abnormal returns by mimicking the portfolios of superior funds.

Hendricks, Patel and Zeckhauser (1993) search for evidence of short-run persistence by studying quarterly returns between 1974 and 1988 for a sample of 165 no-load, growth equity funds. They demonstrate that the superior performing funds (hot hands) in the sample continued to perform well relative to their peers in the near term (one to eight quarters) with most performance persistence in the first year and a reversal thereafter. Similarly, those funds that perform poorly (icy hands) in the most recent year continue their poor performance in the near term, and their performance is more inferior than hot hands’ performance is superior. The authors attribute their results to possible model misspecifications, or to several other plausible conjectures, including: (1) superior fund managers get bid away after building a track record; (2)

following an excessive flow of funds to successful performers, a bloated organization emerges with fewer good investment ideas per managed dollar; (3) once the fund manager establishes reputation, his or her sense of urgency and drive diminishes; (4) market sensitivity of managers is limited to short-term market conditions; and (5) manager salaries and fees rise following recent successes. The authors leave the door open for future researchers to identify the main cause of the observed short-term persistence. In a similar vein, Goetzmann and Ibbotson (1994) explore the then nascent subject of performance persistence. Studying a sample of 728 mutual funds from 1976 to 1988, they find evidence that both top-quartile and bottom-quartile funds in the most recent period experience persistence of returns.

A more comprehensive examination of performance persistence as well as fund expenses and survivorship bias is performed by Malkiel (1995). After studying every diversified equity mutual fund over the twenty-year period of 1971-1991, Malkiel reports that the average fund alpha across this period is -0.06% and indistinguishable from zero. He also finds some evidence for performance persistence during the 1970s, but no such evidence during the second decade under study. He notes that such persistence is likely due to survivorship bias and thus may not be robust.

In a related way, Brown and Goetzmann (1995) investigate a survivorship-bias free database of fund returns for the period 1976-1988 and establish that performance persistence more likely exists because of repeat-losers than repeat-winners, echoing the findings of Hendricks, Patel and Zeckhauser (1993). They suggest that the subjects of cross-fund correlations and the persistence of poor performance merit further research.

Since expected returns and risk vary over time, using unconditional expected returns in any mutual fund performance evaluation model is inherently unreliable. On this basis, in a methodological breakthrough, Ferson and Schadt (1996) use a conditional model of performance evaluation in studying the returns of 67 mutual funds over the period 1968-1990. In their model, the relevant expectations are conditioned on public information variables in the semi-strong sense of market efficiency. This produces alphas with a mean value of zero, which is in contrast with traditional measures of performance that indicate more funds have negative alphas than positive. Ferson and

Warther (1996) take a similar approach in their study of 63 funds and argue that unconditional approaches to performance evaluation lead to the wrong conclusion that managers display positive abnormal performance.

2.3 THE CARHART MODEL AND MORE RECENT STUDIES ON FUND PERFORMANCE

The seminal work by Carhart (1997) is an excellent starting point for the review of more current mutual fund literature. Carhart investigates a survivorship-bias free sample of 1892 equity funds from the relatively long period of 1962-1993.⁵ He classifies the funds into categories of long-term growth and growth-and-income, and studies them using both CAPM and his own four-factor model (Fama-French factors plus one-year return momentum). He finds that the strong persistence in short-term returns is mostly explained by common factors in the four-factor model, predominantly size and momentum. Consistent with previous studies, Carhart finds that the persistence of underperformance by funds in the bottom decile cannot be explained by the common four factors and fund expenses.

Among Carhart's contributions is the explicit test of whether persistence in performance can be explained by common factors in stock returns. Carhart finds a strong positive (negative) relation between the previous one-year momentum and the returns on the best (worst) performing decile of funds. His findings suggest that the portfolios of the best funds are tilted towards past winning stocks, and consequently capture their premium. In a similar way, funds belonging to the top decile tilt their portfolios such that they capture the premium on small stocks.

Development of multi-factor models such as Carhart's model helped explain, among other things, the various style-timing activities that exist in addition to market timing,

⁵ The importance of working with fund data free from survivorship bias is fully explained in Hendricks et al. (1997). The authors demonstrate how studying survivorship-biased data can result in the false discovery of a spurious J-shaped relation between first and second period performances, rather than a monotonically increasing pattern.

namely: size timing, growth timing, and momentum timing.⁶ The importance Carhart placed on fund size, for instance, was followed by many studies focusing on its role in mutual fund performance. Indro, Jiang, Hu and Lee (1999), for example, study 683 funds from 1993 to 1995 for this purpose. While growth in assets under management can result in lower expense ratios and lower turnovers, they report, it can equally be disadvantageous due to higher impact costs, more visibility and administrative complexities. The authors then calculate optimal fund sizes for growth, value and blend funds, respectively \$1.4 billion, \$0.5 billion and \$1.9 billion.

Attempts to deconstruct mutual fund performance continue with Volkman (1999). Through studying a sample of 332 funds from the period 1980-1990, Volkman shows that few funds correctly anticipate market movements during periods of high volatility. However, he claims that many funds still outperform the market through stock selection. Chevalier and Ellison (1999) adopt a different approach to find whether genuine fund manager ability and skill exists. By investigating the cross-sectional patterns in behaviour and performance of 492 fund managers during the period 1988-1994, the authors seek to find if some mutual fund managers in their sample are better than others. Their results suggest that some systematic cross-sectional differences exist that cannot be attributed to differences in managerial behaviour. In particular, they find that managers who attended more selective (higher-SAT) undergraduate institutions have higher performance than others, a result which the authors mainly attribute to differences in inherent stock selection ability, and by extension, reasoning and judgment skills which may explain the difference in the selectivity of their academic institutions in the first place.

Despite the considerable body of literature prior to 2000 demonstrating the aggregate underperformance of actively managed funds relative to passive benchmarks, the empirical question still remained as to why investors continued to invest significant amounts of money in these funds. To find an answer, Wermers (2000) studies the

⁶ Market timing refers to the ability to weigh equity exposures according to one's forecast of future market states. Size timing relates to adjusting the fund's exposure between small-cap and large-cap stocks. Growth timing refers to adjusting exposure along the value-growth continuum. Finally, momentum timing modifies the investment strategy between momentum investing (buying high past-return stocks and selling low past-return stocks) and contrarian investing (doing the opposite).

entire record of stock holdings for all equity funds in the period 1980-2000, together with their turnover and expense ratios, investment objectives, net returns and total assets under management during each fund's history. The results show that during the studied period, mutual funds on average hold stocks that outperform the market by 1.3% per year, which roughly equals their total expenses and transaction costs. In addition, the average net fund return is 1% lower than the CRSP index. Wermers finds that 0.7% of this 2.3% difference between net returns and the return on stock holdings is attributable to lower average return for the non-stock holding component of the portfolio, while fund expenses and transaction costs account for the remaining 1.6%. He posits that part of the higher return for the high-turnover funds is due to the stock-picking skills of the fund managers. In a related way, Chen, Jegadeesh and Wermers (2000) show that growth-oriented funds possess better stock-selection skills than income-oriented funds.

Assuming that fund manager skill exists as some studies suggest, how can this be reconciled with the typical mutual fund underperformance documented extensively in the literature?⁷ Berk and Green (2004) claim that the answer lies in diminishing returns to scale, a phenomenon that funds experience as their assets under management grows. "The failure of managers as a group to outperform passive benchmarks does not imply that they lack skill... [rather] the provision of capital by investors to the mutual fund industry is competitive." The authors identify fund flows and manager changes as two equilibrating mechanisms that play an important role in weakening performance persistence.⁸

⁷ A comprehensive study of the cost of active investing is performed by French (2008). French examines the US equity market over 1980-2006 and finds that, on average, investors spend 0.67% of the aggregate market value each year searching for superior returns. In other words, the typical investor would add 67 basis points to his average annual return by switching to a passive market portfolio.

⁸ The extent of influence these two factors can exert on persistence is examined in Bessler et al. (2010). The authors study a sample of 3946 active US equity mutual funds over the period 1992-2007. They show that the following year risk-adjusted returns of recent winner funds which have not experienced high inflows or departure of skilled fund managers, outperforms by 3.6% relative to those funds suffering from both effects.

In a related way, Pollet and Wilson (2008) explain that a mutual fund typically has two choices when faced with an increase in investor demand: either to increase the number of investments in the portfolio (diversification), or to increase their ownership shares. According to the authors, while most funds choose the latter option, it can be shown that diversification is associated with better performance. Interestingly, they hypothesize that overconfident fund managers either do not diversify at all when facing significant fund inflows, or do not diversify optimally. However, the authors provide no explanation on how to measure overconfidence.

That the rise in assets under management can be detrimental for fund managers is further shown by studying fund managers' trade motivations. For example, Alexander, Cici and Gibson (2007) demonstrate that purely valuation-motivated purchases by managers result in outperforming the market. However, once purchases are made only to invest excess cash from investor inflows, managers do not outperform the market. They record a similar, but weaker effect for stocks that are sold.

Prior to 2006, a key item missing from major mutual fund studies including Carhart (1997) and Wermers (2000) was the explicit identification and modelling of the role of luck in fund performance. The important study by Kosowski, Timmermann, Wermers and White (2006), hereinafter referred to as KTWW, advocates the use of bootstrap techniques in analyzing fund returns, because of the non-normality existing in returns distribution. This non-normality can result from heterogeneous risk-taking across all funds as well the non-normal distribution of individual fund alphas. KTWW contrast previous literature by showing that a sizable minority of fund managers select stocks well enough to "more than" cover their expenses. In their study, the authors use monthly returns of all US open-end domestic equity funds belonging to the 1975-2002 period, one of the largest panels of fund returns data examined to that date. They report that while strong evidence of superior performance and performance persistence exists among growth-oriented funds, managers of income-oriented funds seemingly lack any such ability. After discussing the benefits of bootstrapping, the authors invoke the need for employing this technique in future performance rankings of mutual funds.

Avramov and Wermers (2006) echo the findings of KTWW by showing that predictability in fund manager skill is the primary source of investment profitability, and that active management adds significant value. While most previous studies focus on the US market, Cuthbertson, Nitzsche and O'Sullivan (2008) study UK equity mutual funds over the period 1975-2002. Their results similarly suggest that genuine stock selection skill exists among a relatively small number of superior fund managers. They also show that inferior fund managers are not merely unlucky; rather they demonstrate "bad skill". Consistent with prior literature, the authors find evidence of persistence among loser funds, but not among winner funds.

Among KTWW's findings is that certain growth-oriented fund managers have substantial skill, but the authors do not specify the type of such skill. Jiang, Yao and Yu (2007) employ a holdings-based measure of market-timing for the first time, instead of the returns-based measures which were previously used in the literature and suffered from "artificial timing" bias. They find that, on average, active US domestic-equity fund managers have positive-timing ability. In an attempt to further deconstruct skill, Chen, Adams and Taffler (2009) examine 3181 US growth-oriented equity mutual fund over the period 1993-2006. They show that growth timing is the main contributor to the persistent abnormal returns reported by KTWW. The authors also demonstrate that successful growth timing is confined to those managers who invest predominantly in growth stocks.

While key studies such as KTWW, Avramov and Wermers (2006) and Fama and French (2010) discuss the existence of outperforming or underperforming mutual funds in the extremes, they are not particularly helpful in explaining the distribution of skill, or lack of it, in the entire fund population. Barras, Scaillet and Wermers (2010) attempt to address this issue in their study of 2076 actively-managed domestic equity mutual funds between 1975 and 2006. Their results suggest 75% of funds exhibit zero-alpha, i.e. they are neither skilled nor unskilled, which is consistent with the equilibrium discussed in Berk and Green (2004). The authors also find a significant proportion of positive-alpha (skilled) funds prior to 1996, but almost none by 2006.

Although the subject of performance evaluation and persistence has been more or less studied with regards to investment vehicles other than mutual funds, the research findings do not point in the same direction. For example, performance in institutional investment management has recently attracted equally-deserved attention. In one of the latest studies on the subject, Busse, Goyal and Wahal (2010) investigate the performance of 4617 actively-managed domestic equity institutional product between 1991 and 2008. They reveal that only modest evidence of persistence exists in the Fama-French three-factor model, and little to none evidence when momentum is taken into account. As for hedge funds, recent studies e.g. Jagannathan, Malakhov and Novikov (2010) have found evidence of significant performance persistence among superior funds, but little or no such evidence among inferior funds, which appears to contrast parallel literature in mutual funds.

2.4 THE GENERAL PARADIGM OF THE OVERCONFIDENCE EFFECT

The objective of this section is to survey the evidence on the overconfidence effect in its more general context and set the scene for the following section which discusses the applications of overconfidence in the domain of finance.

The terms “confidence”, “trust” and “full belief” are usually considered synonyms.⁹ The level of collective trust and confidence among individuals can demonstrably have significant impacts on their group behaviour. The dynamic between one individual’s level of trust and another’s is a particularly interesting area of research. For example, Akerlof and Shiller (2009), in their book *Animal Spirits*, propose using *confidence multipliers* to arrive at a general model of how confidence spreads in a group.¹⁰

⁹ In fact, “confidence” is derived from the Latin *fido* meaning “I trust”. The credit crisis we have just witnessed is also described as a confidence crisis, and it is interesting to observe that “credit” is similarly derived from the Latin *credo* meaning “I believe”.

¹⁰ They base this on the idea of Keynesian multipliers that model how marginal propensity to consume spreads in a population of investors in response to, for instance, a government stimulus. They argue that a marginal change in person A’s level of confidence affects person B’s level of confidence to a

On an individual level, 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.¹¹ 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 endeavour 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 observation that individuals tend to be overoptimistic about future events and the consequences of their actions; and finally, *illusion of control* indicates that people think they have more influence than they actually do over the outcome of a random or partially random event.

Overconfidence is very widely researched in psychology. “No problem in judgment and decision making is more prevalent and more potentially catastrophic than overconfidence”, Plous (1993) concludes. The concept of overconfidence, however, is not uniquely defined in prior literature. Moore and Healy (2008) reconcile three common but distinct definitions of overconfidence, which, in decreasing order of citation in the literature, are: (1) *overestimation* of one’s actual level of ability, performance, chance of success, or level of control; (2) *overprecision* (excessive certainty) in the accuracy of one’s beliefs, also called *miscalibration* and (3) *overplacement* of one’s ability, etc. relative to others, also known as the *better-than-average effect*. While overestimation and overplacement are often considered equivalent manifestations of self-enhancement, there is also some inconsistency between them such that those domains contributing to strongest overestimation usually produce the least overplacement and vice versa.

similar extent multiplied by the relevant consumption multiplier. In this way, they propose a simple mathematical framework to model how confidence or lack of it can quickly spread among individuals.

¹¹ This effect has been extensively studied in the psychology literature. A number of key papers in this relation have been cited in Gervais and Odean (2001).

Moore and Healy (2008) propose a theory to deal with this apparent contradiction. They posit that individuals often have imperfect information about their own performance and ability, yet have even worse information about others. Therefore, while people's self-estimates are regressive, their estimates of others' abilities are even more regressive. As such, when faced with difficult tasks, people overestimate their abilities, overestimate others even more, and thus believe they have performed (or will perform) worse than others. On the other hand, when faced with easy tasks, people underestimate their own performance while underestimating others even more, which leads them to believe that they are better than others. This distinction also serves to explain the prevalence of underconfidence (particularly underestimation and underplacement) in circumstances where subjects are faced with easy tasks. This confirms the view held by Klayman, Soll, Gonzalez-Vallejo and Barlas (1999) who summarise the results of many studies as "the confidence people have in their judgments exceeds their accuracy and that overconfidence increases with the difficulty of the task."

Prior psychology literature produces different types of explanations for the overconfidence effect. Mostly, these phenomena have been interpreted in the framework 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. On the other hand, a challenging view has been put forward by *cognitive* psychologists. They claim that people generally expect to succeed, and they generally accept responsibility for their expected outcomes. Hence, in combination of the two effects, people tend to be prone to self-serving attribution bias which, in turn, engenders overconfidence.

Another strand of psychology literature offers two alternative categories of explanations for overconfidence. The first view highlights biases in information processes, hypothesizing that individuals aiming to arrive at a decision search for relevant information in their memories in order to reach a preliminary conclusion. Then, they proceed to search selectively for further evidence consistent with their initial conclusion which, of course, results in overconfidence. The second

explanation emphasizes the role of unbiased judgmental error in generating overconfidence. A detailed discussion of this perspective can be found in Moore and Healy (2008).

Whatever the underlying psychological mechanisms that produce overconfidence, there is an ongoing debate as to whether overconfidence is static or dynamic. Glaser and Weber (2010) elicit a number of factors that are considered to have an influence on the actual level of an individual's overconfidence as well as how it is measured. These factors include the specific elicitation method used, the difficulty level of questions asked, gender, culture, the amount of available information, monetary incentives, and expertise. I will briefly discuss how these factors can potentially affect overconfidence, and how this may be relevant to the current study.

First, in terms of the *elicitation method*, interval estimates (also known as the fractile method) and direct probability judgments are two common approaches used to measure overconfidence. Studies that use interval estimates (e.g. by asking the subjects to estimate the length of the Nile river or the future value of the S&P 500 index within a 95% confidence interval) often find very tight probability distributions (see Lichtenstein, Fischhoff and Phillips (1982) and Keren (1991) among other studies). On the other hand, only a modest bias is induced by direct probability judgments, as Glaser and Weber (2010) explain. Hence, the method used to measure miscalibration strongly influences the degree of evaluated overconfidence.

Second, the *difficulty level* of the questions asked from subjects also influences the measurement of overconfidence. As discussed above, overconfidence is often diminished, or even reversed, when subjects are faced with very easy questions. This phenomenon, first documented by Lichtenstein and Fischhoff (1977), is also known as the *hard-easy effect*.

Third, *gender* is often cited as an important distinguishing variable in overconfidence research. Men are generally considered more overconfident than women, while general differences among the two groups are highly task-dependent. (see Barber and Odean (2001) among others).

Fourth, *cultural variations* exist in the level of observed overconfidence among different nations. For example, studies indicate that the Chinese are generally more overconfident than the Americans which may be due to the Americans' tendency and cultural predisposition to challenge others as well as their own opinions (see Yates, Lee and Bush (1997) as an example).

Fifth, the *amount of information* and *monetary incentives* provided in experimental settings is shown to affect the degree of observed overconfidence. For example, the availability of more information is associated with increased overconfidence since, as Glaser and Weber (2010) explain, "subjects do not adjust for the cognitive limitations that reduce their ability to effectively use additional information."

Sixth, the effect of the subject's *level of expertise* on their judgement and decision-making is the topic of an ongoing debate. Glaser and Weber (2010) summarise a substantial body of research suggesting that overconfidence proxied by miscalibration is equally common among experts in most domains, although certain underlying mechanisms may be different. For instance, with regards to interval estimates, although both novices and experts demonstrate similar levels of overconfidence, experts report narrower intervals (which decrease the estimation hit rate) but report midpoints closer to the correct value (which increases and thus balances the net effect on overconfidence).

2.5 OVERCONFIDENCE IN THE DOMAIN OF FINANCE

Investors have a general tendency to falsely attribute superior past performance to their own skill, and inferior past performance to chance, which produces overconfidence (Gervais and Odean, 2001). Overestimation of one's investment skill, in this manner, can have a wealth-diminishing effect, as documented by Odean (1999) and Barber and Odean (2000) who study this phenomenon among traders. They demonstrate that excessive trading following increased confidence often results in decreased investment performance.

A similar pattern seems to work with regards to analysts. Hilary and Menzly (2006) explain how: Analysts become overconfident in their ability to predict future outcomes after having made a random series of good predictions. As a result, they allocate excessive weight to their private information and less so to public signals including market reactions and other analysts' forecasts. Therefore, their subsequent prediction is likely to be less precise, reducing the probability for their next forecast to be better than the competition. This, in turn, can trigger negative feedback such that overconfidence is reduced. Hence, this is a short-term, cyclical pattern the intensity of which varies with the analyst's performance. The authors emphasize that "analysts acting under this form of overconfidence do not necessarily underperform relative to other analysts but rather they underperform compared to their own expected performance." A possible scenario may even be that overconfident analysts consistently outperform others if the effect of overconfidence relative to other attributes such as "skill" happens to be small.

With regards to investors, a commonly used proxy to gauge overconfidence is trading activity. Although trading activity as a proxy of overconfidence clearly works for retail investors, it cannot be as easily used for fund managers and other professional investors. 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 (2011) 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 reduces subsequent performance. However, one should note that other potential confounding factors may affect managerial trades, such as incentives 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.

Apart from the high levels of trading volume, other predictions have also been made in the literature concerning the financial effects of overconfidence. For example, Odean (1999) finds that overconfident traders hold undiversified portfolios and have lower expected utility than rational traders. Caballe and Sakovics (2003), similar to Odean, explain the excess volatility of asset prices by the presence of overconfident traders. In a related way, Scheinkman and Wei (2003) provide evidence suggesting that overconfidence can explain the formation of bubbles in financial markets.

Active Share is another proxy used in the literature for measuring investor overconfidence. It 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, neither fund turnover nor *Active Share* is a “clean” measure of overconfidence, since a number of factors briefly discussed above potentially confound the link between these measures and investment performance. For example, defining an optimal fund-specific benchmark against which to measure the *Active Share* of a fund manager is challenging.

A more straightforward way of measuring investor overconfidence may be to examine their actual estimates and predictions about their subsequent performance. Willis (2001), for examples, investigates annual earnings forecasts that are publicly released in conjunction with mutual fund manager stock recommendations, and finds 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 this 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 such secondary data collections.

2.6 OVERCONFIDENCE AND PERFORMANCE: RELATED EVIDENCE FROM SPORT PSYCHOLOGY

It can be helpful to explore the impact of confidence on an individual's performance in other areas of activity and look for comparable patterns of judgement and decision making. One such area is sport psychology. Professional investors are similar to professional athletes in a number of ways, e.g. both groups of individuals (1) are expected to outperform on a consistent basis; (2) are aware on one level that this is not always possible (classic cognitive dissonance) and that luck play an important role in their results; (3) work under extreme pressure and intense competition; (4) have to rely to a great extent on subjective judgement, intuition and gut feeling; and finally, (5) are under constant threat of dismissal if they underperform.¹²

However, some differences also exist between professional investors and professional athletes in this context. For example, the environmental factors affecting sporting competitions are arguably less complex than those affecting the performance of financial markets. In addition, it is demonstrably easier to distinguish and measure athletic skill compared to "investment skill." For example, a basketball player who consistently scores around 95% of penalty throws in a number of consecutive games can more easily be described as skilled since (1) the circumstances of the experiment remain unchanged, (2) all players are subject to the same conditions, (3) all players employ equal assets and (4) the impact of players' decisions are often immediately observable.

In this context, it may be useful to see how confidence may have any role in the performance of professional athletes. Both coaches and high-performing athletes invariably agree that self-confidence is crucial to individual and team success. There is both anecdotal and scientific evidence supporting this observation (see Burton (1988) among others). In a more comprehensive study, Burton and Raedeke (2008) explain that self-confidence enhances performance through its relationship with three other characteristics: anxiety, motivation, and concentration.

¹² There are appears to be interesting links between the literature on tournament behaviour of fund managers and its parallels in competitive sports which provides another potentially rich avenue of research in the context of this study.

High self-confidence is often associated with low mental *anxiety*. Athletes enjoying optimal self-confidence experience fewer worries and self-doubts compared to other athletes. This results in positively interpreting high arousal as readiness or excitement (see figure 1).

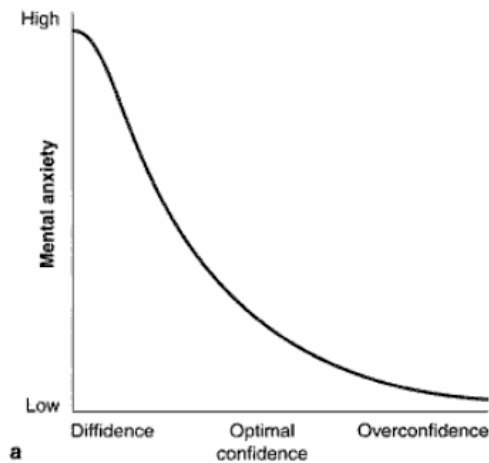


Figure 1: The anxiety-confidence dynamic

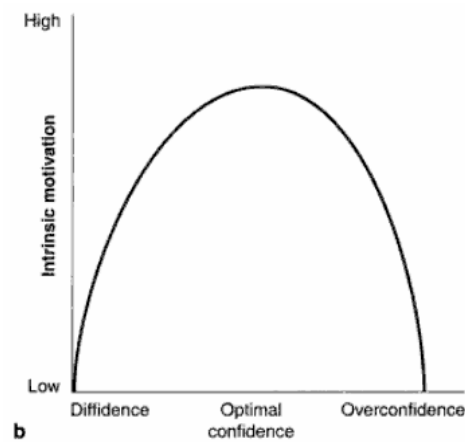


Figure 2: The motivation-confidence dynamic

In addition, athletes with optimal self-confidence are highly *motivated* to develop their game and continue their success record. On the other hand, while diffident (under-confident) athletes do not feel competent enough to be optimally motivated

which, in turn, diminishes their performance and traps them in a vicious circle, overconfident athletes feel they are so talented that they do not need to improve their game. Finally, optimally confident athletes often have an optimal level of *concentration* on their game. Their confidence helps them block out most distractions and “focus on the attentional cues necessary to play their best” (Burton and Raedeke, 2008). See figures 2 and 3.

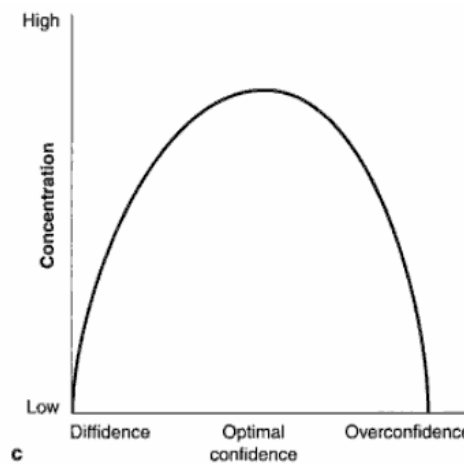


Figure 3: The concentration-confidence dynamic

The overall effect of the above three mechanisms results in the performance of professional athletes having an inverted-U relationship with their confidence. Therefore, one can distinguish the ideal level of self-confidence (optimal confidence) from too little confidence (underconfidence or diffidence) and too much confidence (overconfidence). While optimally confident athletes are prepared and competent, and have all the required mental and physical skills to achieve their realistic goals, diffident athletes expect to fail because they lack or underestimate their preparation and competence, which, in turn, leads them to feel underconfident and contributes to actual failure through the self-fulfilling prophecy. Diffident athletes often underachieve due to lack of confidence which both limits their development and their performance.

Burton and Raedeke also argue that overconfident athletes are the most difficult group to coach. They distinguish athletes with *inflated confidence* from those with *false confidence*. Inflated confidence refers to the situation where athletes sincerely believe they are better than the competition, which can be due to pampering, excessive media hype, or playing against weak competitors. While these athletes are often very good, they often become complacent and their once-superior skills fail them through lack of preparation, “leaving them wondering what happened and why they felt so lethargic, out of sync, and off their game.”

False confidence, on the other hand, is observed among athletes who believe that pretending to be confident on the outside helps them overcome their underconfidence and fear of failure on the inside. Falsely confident athletes are often considered “brash, cocky, and pretentious, but their arrogant facade is designed to mask their self-doubts” (ibid). They avoid situations threatening their fragile self-confidence, often misrepresent reality, and fall prey to simplistic positive thinking.

No matter which type of overconfidence affects athletes, their performance suffers as predicted by the inverted-U relationship between performance and level of confidence. However, an optimal level of self-confidence is needed for athletes to reach their true potentials. Burton and Raedeke recommend four strategies for enhancing self-confidence: performance accomplishments, vicarious experience, verbal persuasion, and arousal control. The functioning of these four strategies can be summarized in figure 4 below.

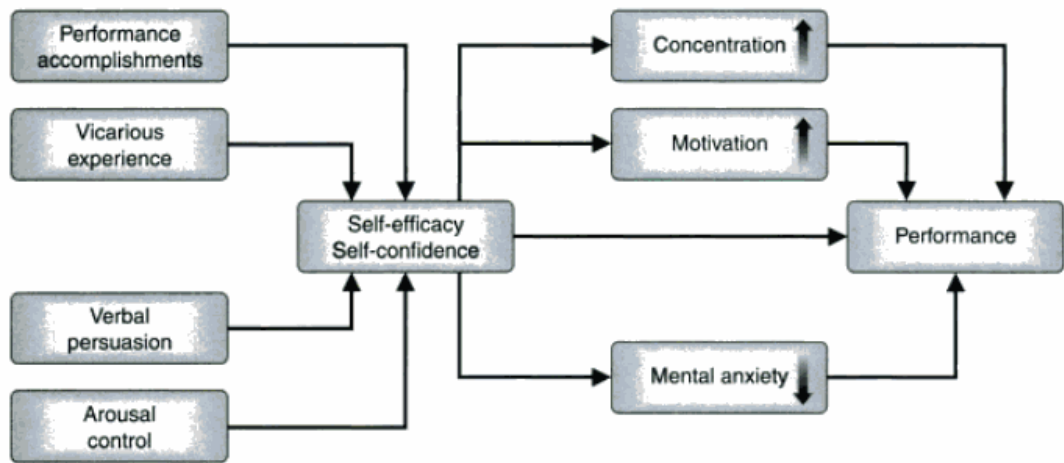


Figure 4: How self-confidence enhances performance in competitive sports

Performance accomplishments refer to athletes taking credit for their success as a reflection of their hard work and ability. The consistency of past successful experiences, their recency, and their quality contribute to the development of confidence in the athletes. A systematic *goal-setting* program helps athletes develop a strong history of performance accomplishments. *Vicarious experience* refers to helping athletes experience success indirectly, whether through modelling (watching others demonstrate how to perform a skill or strategy) or through imagery (a type of self-modelling, in which athletes form a mental idea of how to perform a skill or mentally rehearse a well-defined skill) since imagined success is a powerful confidence builder. *Verbal persuasion* includes all forms of compliments, positive feedback from coaches, teachers, teammates, parents, the media, and even positive self-talk. Finally, *arousal control* indicates the athlete's level of control over physiological symptoms associated with readiness which can be interpreted negatively as anxiety or positively as excitement.

2.7 THE CONCEPTUAL MODEL AND RESEARCH QUESTIONS REVISITED

The aim of this section is to integrate the above strands of literature to provide a conceptual model that serves to motivate the research questions approached in the current study. 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 the decision-making behaviour of professional investors. In particular, due to the fact that the bulk of investment in financial markets is made by institutional (supposedly sophisticated) investors rather than retail 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.

In such settings, it is reasonable to investigate to what extent mutual fund managers, as a fairly representative sample of professional investors, are prone to behavioural biases such as overconfidence. In the current research, the extent to which overconfidence and related behavioural traits e.g. over-optimism, narcissism, self-serving attribution, etc. may have any bearing on fund performance is of interest.

The substantial body of literature on overconfidence appears to suggest that, in principle, through the self-serving attribution bias, investors falsely attribute superior past performance to their own skill, and inferior past performance to chance (see Gervais and Odean (2001) for example). When performance is deemed poor and unsatisfactory, either relative to peers or in absolute terms depending on the manager's perspective and the fund's mandate, the fund manager is confronted with overwhelming emotional pressures in the form of fear, stress and anxiety. As explained before, several academic studies in psychology, inspired by Freud (1936), suggest that such pressures can negatively affect cognition by weakening, distorting, or delaying the process of true information signals.

On the other hand, as was pointed out in the previous sections, the bulk of prior research on overconfidence concurs that increased levels of this variable can lead to higher trading volumes and increased frequency of making investment decisions which, in turn, diminishes future performance. A summary of these studies can be found in Choi and Lou (2008).

Hence, the above arguments seem to have the overall conclusion that past investment performance surely affects the investor's level of confidence, which in turn impacts

future investment performance. The net dynamic effect of these processes on overconfidence depends on the record of past results, i.e. whether the fund manager has experienced a round of recent good or recent bad results. Therefore, in a randomly alternating round of positive and negative returns, one may expect the average fund manager's level of overconfidence to increase, *ceteris paribus*. I have developed the following simple system dynamic model to illustrate this point.

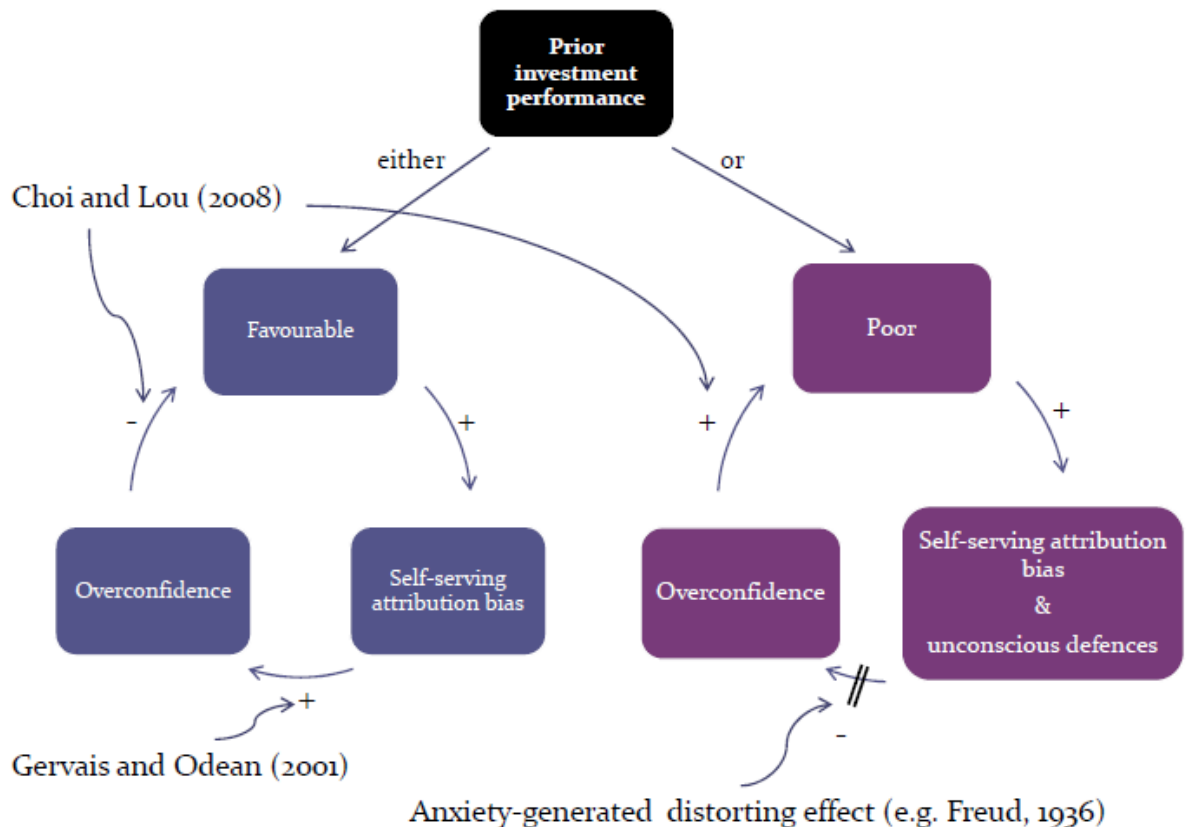


Figure 5: The interaction between self-attribution bias, overconfidence and performance

The model proposed by Gervais and Odean (2001) is essentially a learning model. They develop a multi-period market model that describes “both the process by which traders learn about their ability and how a bias in this learning can create overconfident traders.” They assume, in their model, that traders initially do not know their ability and that they *learn* about it through experience. Gervais and Odean argue that traders who accurately forecast next period dividends update their beliefs improperly, i.e. they overweight the probability that their success was due to

skill or superior ability, hence becoming overconfident in the process. This is a dynamic model in which a trader's level of overconfidence changes according to his or her successes and failures.

However, an element missing from the Gervais and Odean model is, supposedly, the rise in a trader's or fund manager's level of expertise and familiarity with how financial markets operate. The evidence in this area is rather mixed. There exist some studies showing that more experienced fund managers are less prone to self-serving attribution bias and overconfidence (see Locke and Mann, 2001; Christoffersen and Sarkissian, 2002 among others). However, a different set of studies indicate that compared to relatively inexperienced individuals, experts are more likely to be overconfident (see Heath and Tversky, 1991; Glaser et al, 2004 among others). Taking a different approach, Hirshleifer and Luo (2001) recognize that the self-serving bias in the learning process explains the persistence of overconfidence and its importance in "a dynamic steady state even if overconfident traders lose money." However, their approach differs in that they do not allow a trader's confidence to grow over time although they allow overconfident traders to thrive profitably.

In brief, there is no clear evidence concerning the impact of experience on the behaviour of fund managers. This is, among other reasons, due to a heterogeneous set of definitions provided for overconfidence in prior research as well as the inherent difficulty of measuring possible outcomes of the learning process in a robust way (Menkhoff et al, 2006).

In essence, several of my research questions are closely related to the components of the model displayed in figure 5. Let us revisit the research questions that this study seeks to answer:

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. How does the self-attribution bias interact with overconfidence and investment performance?
4. How does self-attribution bias driving overconfidence manifest itself in the way fund managers communicate their investment results to their clients, in particular by engaging in “storytelling”?
5. How does the above process relate to the anxieties generated by having to explain, justify and cope with poor past performance as well as a highly uncertain working environment?

The first three research questions are closely related to the model above. In fact, chapters 6 and 7 address the first three research questions. The last two research questions are addressed in chapter 5. The following chapter, chapter 3, focuses on the development of the research hypotheses, research variables and a detailed discussion of the research methodology.

CHAPTER 3 - RESEARCH HYPOTHESES AND METHODOLOGICAL APPROACH

3.1 INTRODUCTION

The previous chapter concluded by laying out the conceptual model used in this study and the research questions derived from the literature. This chapter will introduce the research hypotheses that will be tested in subsequent empirical chapters. I will discuss in detail the key variables used in the hypotheses. Further, I will explain the research methods used in the study in terms of collection and analysis of the research data.

The chapter is organised as follows: Section 3.2 explains the process of developing the research hypotheses based on the review of literature in the previous chapter. Sections 3.3 and 3.4 discuss the research variables. Section 3.5 introduces the research methodology in detail including the stages of data collection and data analysis.

3.2 DEVELOPMENT OF RESEARCH HYPOTHESES

My null hypotheses about the link between fund manager overconfidence and the performance of investment decisions are developed in this section. I group the hypotheses into three broad groups, the impact of prior investment performance on fund manager overconfidence, the potential impact of fund manager overconfidence on subsequent investment performance, and the link between performance and other narrative based variables including tone and readability. As I will explain later, abnormal values of tone and readability are closely related to overconfidence; however, these two variables cannot be interpreted as overconfidence proxies since they are fundamentally distinct constructs.

3.2.1 THE IMPACT OF PRIOR PERFORMANCE ON OVERCONFIDENCE

Prior research outlined in the previous chapter broadly concurs that an individual experiencing a round of positive outcomes associated with her decisions tends to become overconfident. Thus, it is reasonable to expect the same pattern to hold for the investment decisions of fund managers, i.e. those fund managers whose funds have experienced higher investment returns should, on average, become more overconfident than their peers. As I explain in detail later in this chapter, I use three proxies (overoptimism, excessive certainty, and excessive self-reference) to measure overconfidence. Hence, three null hypotheses are developed and grouped into a single null hypothesis below:

H₁₀: There is no significant difference in the *optimism/certainty/self-reference* scores of fund managers whose funds have experienced varying levels of prior performance, *ceteris paribus*.

3.2.2 THE IMPACT OF OVERCONFIDENCE ON SUBSEQUENT PERFORMANCE

The vast body of research on overconfidence introduced in the previous chapter uniformly agrees that increased overconfidence leads both retail and professional investors to trade more frequently which, on average, diminishes their returns. Other more subtle mechanisms may also be at play which adversely affect overconfident investor decision-making ability. One such mechanism can be due to the potentially “phantastic” nature of investments in general. In other words, even “sophisticated” fund managers can develop “love-hate” relationships with their investments and therefore not sufficiently consider the associated risks of investing in them.¹³ Hence, everything else being equal, one may expect an increase in fund manager overconfidence to be associated with diminishing investment returns in the subsequent months. Again, using the three overconfidence proxies, we develop the following hypothesis:

¹³ As a case in point, Eshraghi and Taffler (2012) argue that the recent hedge fund “bubble” and its collapse in 2008 was to a large extent driven by such emotions.

H2₀: There is no significant difference in the future investment performance of mutual funds whose managers exhibit varying degrees of *overoptimism/certainty/self-reference*, ceteris paribus.

3.2.3 THE LINK BETWEEN PERFORMANCE, FUND MANAGER TONE AND REPORT READABILITY

A growing body of literature in finance and accounting seeks to measure the tone and sentiment of corporate annual reports, newspaper articles, press releases, and investor message boards using textual analysis. Examples of some recent studies include Engelberg (2008), Li (2008), Tetlock, Saar-Tsechansky and Macskassy (2008), Sadique, In and Veeraraghavan (2008), Brockman and Cicon (2009), Loughran and McDonald (2010), Amernic, Craig and Tourish (2010), Demers and Vega (2010) and Loughran and McDonald (2011).

The above studies generally point to the conclusion that negative word classifications can effectively measure tone, and can be significantly correlated with other financial variables. It is often argued that negative words can be more meaningful for content analysis purposes compared to positive words, since positive words occur more frequently in annual letters to shareholders regardless of the corporation's financial position. This is consistent with the well-documented *Pollyanna* effect which, as Boucher and Osgood (1968) define, asserts that "there is a universal human tendency to use evaluatively positive words more frequently and diversely than evaluatively negative words in communicating." Another drawback of positive words includes their use in conveying negative news, e.g. by utilizing negated positive words such as "not good" or "did not improve" (Loughran and McDonald, 2010).

Among the relevant studies, the topic of CEO tone (or "tone at the top") has been frequently investigated. Cunningham (2005) defines tone at the top as "the shared set of values that an organisation has emanating from the most senior executives. It can be reinforced with written codes, and other policies and documents, but, more importantly, it reflects the actions of these executives. Are they 'walking the talk'?" Tone at the top not only sets the corporate culture, but also reflects the nature of CEOs.

Arguably, the tone and rhetoric of fund managers can be analysed in a similar vein. Fund managers often play the role of CEOs for the funds they manage, i.e. they are solely and fully responsible for the performance of their investments. Fund managers report to their investors on all aspects of performance, much in the same way that a corporate executive reports on the performance of a company. As such, fund-manager-speak should be akin to CEO-speak.

The general pattern of conclusions drawn in the past studies concerning tone is the following: Qualitative (soft) earnings information proxied by tone and other associated variables can additionally predict asset prices beyond the predictability in quantitative (hard) information (Engelberg, 2008). For example, the optimistic or “surprise” tone of earnings forecasts is positively correlated with the magnitude of subsequent abnormal returns (Brockman and Cicon, 2009). Davis, Piger and Sedor (2008) also find that managers use optimistic and pessimistic tone in earnings press releases to provide information about the firm’s expected future performance and investors respond to such disclosures, while Tetlock et al. (2008) demonstrate that the fraction of negative words in firm-specific news stories predicts low earnings. Sadique et al. (2008) also study earnings press releases and find that positive tone increases returns and decreases volatility while negative tone decreases returns but increases volatility. More generally, Demers and Vega (2010) find that it takes investors longer to interpret this soft information component compared to the hard information in financial disclosures.

Based on the above arguments, one expects similar effects to link fund manager tone with fund performance, i.e. superior past performance may inspire a comparatively more positive and hubristic tone by the fund manager. Excessive levels of such positive tone may provide an alternative proxy for overconfidence and may similarly affect subsequent returns.

Finally, in terms of readability, it is widely agreed that narratives conveying a negative message or poor news are generally less readable than others. Firms with lower earnings have annual reports that are harder to read (Li, 2008), while the management is more straightforward in disclosing information when the firm is doing respectively well. This association between performance, disclosure

readability and other lexical features is often explained by strategic reporting and impression management incentives. In a related way, the simultaneous presence of low reading ease and high variability in readability, also known as *obfuscation* (Curtis, 2004), is an equally pervasive phenomenon in corporate annual reports. On this basis, I propose the following research hypothesis:

H3₀: There is no significant difference in the *tone/readability* of fund manager commentaries whose corresponding funds have experienced varying degrees of past investment performance, *ceteris paribus*.

Hypotheses 1 and 3 are tested in chapter 5 and chapter 6 while several forms of hypothesis 2 is tested in chapter 7. The rest of this chapter introduces the operational definitions of the research variables, and includes a detailed discussion of the research methods employed.

3.3 MAIN RESEARCH VARIABLES

This section introduces the variables used in the research hypotheses and discusses their measurement. Of the five main research variables, three are measured directly using the DICTION software, while the remaining two are calculated by other methods. DICTION is a content analysis software that is widely used in the field of finance and accounting (see Appendix 3) to produce consistent narrative-based scores for any given text. It has been extensively used to analyze the speeches of policymakers, political speeches, earning announcements and corporate annual reports.

The DICTION algorithms use a series of thirty-three dictionaries (word-lists) to search text passages for five main semantic features (Activity, Optimism, Certainty, Realism and Commonality) as well as thirty-five sub-features (e.g. Praise, Blame, Denial, etc). DICTION employs a 10,000-word corpus and the user can create additional custom dictionaries for specific research purposes. The program provides both alphabetic and numeric output files which include raw totals, percentages, and standardized scores and extrapolations to a 500-word norm for small input files. For

each of its forty scores, DICTION also reports normative data based on a 20,000-item sample of contemporary discourse. One can use these general norms for comparative purposes or select from thirty-six sub-categories, including speeches, newspaper editorials, business reports, etc (DICTION 5.0 User's Manual, 2010).

The **first** main research variable used in this study is optimism. 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". Further details about OPTIMISM and other master variables are included in Appendix 1.

The normal range of OPTMISM scores calculated in this way depends on the reference dictionary used. For example, based on the *Corporate Financial Reports* dictionary,¹⁴ which may be appropriate for the purposes of this study, the normal range falls between 47.92 and 52.50. In other words, texts belonging to the category of Financial Reports are expected, on average, to have an OPTIMISM score distribution with a standard deviation range of 47.92-52.50 centred on the mean. Other viable choices for reference dictionaries include the *Corporate Public Relations*¹⁵ dictionary and the *Financial News*¹⁶ dictionary.

The **second** research variable used in this study is certainty. DICTION defines CERTAINTY as "language indicating resoluteness, inflexibility, and completeness and a tendency to speak ex cathedra." The formula for calculating CERTAINTY is: [tenacity + levelling + collectives + insistence] - [numerical terms + ambivalence +

¹⁴ This dictionary is a sampling of annual financial reports from a variety of Fortune 500 companies, including 3M, Ford, Merck, Dynatech, etc. Reports were collected electronically from such internet sites as Annual Reports Library, Index: Annual Report Gallery, and Barron's Annual Report and Earnings Service.

¹⁵ This dictionary is a broad-based collection of official mission statements, public pronouncements, and CEO speeches on behalf of major American corporations from the 1960s through the mid-1990s. Includes manufacturing companies (e.g., Boise-Cascade), mining and construction (e.g., Flour Daniel), transportation and telecommunications (e.g., AT&T), as well as, financial and service-based industries (e.g., Federated Department stores, H&R Block, etc.).

¹⁶ This dictionary is a variety of news stories related to financial issues (e.g. tax returns, market predictions, trends in stocks and bonds, tax law, speculation on specific annuities, etc.) obtained from the online publications of Forbes, The San Francisco Chronicle, the Daily News Bulletin, etc.

self-reference + variety]. I apply the adjustment proposed in Demers and Vega (2010) to include numerical terms as adding to rather than subtracting from the CERTAINTY score. Appendix 1 includes detailed definitions of the sub-categories used in this formula.

The **third** variable used in this research as a proxy for overconfidence (and by extension, narcissism) is self-reference. Chatterjee and Hambrick (2007) use the percentage of all first person singular pronouns appearing in company press releases as a measure of CEO narcissism. Since fund managers rarely refer to themselves in fund commentaries in the singular format, I define SELF-REFERENCE as “the number of first person pronouns as a percentage of all words” in a given text. In other words, the frequency of all occurrences of *I, I'd, I'll, I'm, I've, me, mine, my, myself, we, we'd, we'll, we're, we've, us, our, ours, ourselves* are calculated and added, and then normalized for the length of the text. In the empirical analysis in Chapter 7, I explore the possibility of constructing a meta-variable comprising some or all of the overconfidence proxies discussed above.

And **fourth**, I seek to measure the tone used by the fund manager in her commentary. The conventional approach to measuring tone of a narrative is to use word classifications. For example, *positive/negative tone* can be defined as a function of positive and negative words mentioned in a text. Similar classifications can be used for words indicating a diverse range of themes such as *uncertainty, litigation, strong modality, and weak modality*.

I use the approach adopted by Loughran and McDonald (2011) that employs positive and negative word lists developed by the authors. While the Harvard Dictionary is often used in prior studies, it is more suitable to research in the fields of psychology, sociology and other related disciplines. Furthermore, Loughran and McDonald (2010) find that almost three-fourths of the words identified as negative by the Harvard Dictionary do not have a negative connotation in a financial context. Words such as *liability, taxing, foreign*, etc. belong to the misclassified list. In addition, the authors exclude simple negation (*no, not, none, neither, never, nobody*) from their negative word list. Hence, I use their word lists to define the TONE variable as “the number of positive words minus the number of negative words, divided by the sum

of words in both categories.” Therefore, the range of this variable is -1 to +1 and measures the relatively positive tone of the narrative.

3.4 CONTROL VARIABLES

Control variables are used to ensure that the test of the relation between the dependent variable and the independent variable is not confounded by other factors. In this section, I discuss the control variables used in the empirical model. The control variables are essentially the firm-specific characteristics in the Carhart model which is an augmented Fama-French asset-pricing model.

The **first** control variable used in this study is the *market factor* (excess returns) which is captured by the market beta. The role of the market beta in explaining average returns is well documented across the finance literature. Some of the key studies that have supported this effect include Black, Jensen and Scholes (1972) and Fama and MacBeth (1973).

The **second** control variable in this research is *firm size*. Several studies e.g. Banz (1981), Reinganum (1982) and Herrera and Lockwood (1994) suggest that firm size is a dominant factor that has additional explanatory power for average returns. In their key study, Fama and French (1993) form factor-mimicking portfolios to develop a risk factor for firm size known as SMB (Small minus Big). SMB effectively measures the size premium i.e. the return on a portfolio of small stocks minus the return on a portfolio of big stocks.

The fund's *investment style* is the **third** control variable used in the regression model. Similar to size, the effect of investment style is widely researched by such studies as Rosenberg, Reid and Lanstein (1985) as well as Chan, Hamao and Lakonishok (1991). The risk factor developed by Fama and French (1993) for this effect is known as HML. HML measures the value premium i.e. the return on a portfolio of value stocks minus the return on a portfolio of growth stocks.

3.5 RESEARCH METHODOLOGY

This section introduces the research methodology used in this study. First, the data collection process is briefly outlined. More details on the data collection process are provided in Chapter 4 which includes a full discussion of data sources. Finally, the data analysis methods are explained in detail.

3.5.1 DATA COLLECTION

The research data is collected from a number of sources. The mutual fund annual reports are sourced from the EDGAR online database provided by the Securities and Exchange Commission. It collects a wide range of mandatory and voluntary disclosures for US companies and individuals. A full description of this database is provided in Chapter 4.

A key stage of collecting annual reports is downloading them from the EDGAR database. Clearly, manually downloading a large number of reports can be very time consuming. I automated this process in the following way. EDGAR is archived periodically and the archived filings are accessible through the ftp protocol. Fortunately, the web addresses of these filings are reasonably well-structured. In other words, by knowing the identifier of a given company and the year of an annual report, one can generate the address where the said report can be downloaded. Therefore, in principle, a computer program that can automatically read and save a list of web addresses in a predetermined location can resolve this issue. In collaboration with an IT expert,¹⁷ such a computer program was prepared and tested. This computer code can be found in Appendix 4.

The mutual fund returns and other financial figures are mainly extracted from the CRSP Survivor-bias free Mutual Fund Database. This database is widely referenced in finance and accounting scholarly research and is available through the WRDS platform. More details on this database and the associated data collection procedures are provided in Chapter 4.

¹⁷ I gratefully acknowledge advice and assistance from Dr. Mark Greenwood at Manchester Business School.

3.5.2 DATA ANALYSIS

This section introduces two of the main data analysis methods used for empirical research in this study. The first section discusses the content analysis methodology that is used to analyse the fund manager commentaries. The second section describes the analysis method used to deconstruct mutual fund performance using a regression model.

3.5.2.1 CONTENT ANALYSIS OF FUND MANAGER NARRATIVES

Krippendorf (2004) defines content analysis as “a research technique for making replicable and valid inferences from texts (or other meaningful matter) to the contexts of their use.” As a research technique, content analysis is often praised for being objective, systematic and replicable. It is based on the assumption that the language people choose to express themselves in contains information about the nature of their psychological states, an assumption implying a presentational or descriptive model of language (Viney, 1983).

What sets content analysis apart from other similar research techniques, according to Krippendorf (2004), is that content analysis is (1) an unobtrusive technique; (2) capable of accepting unstructured material; (3) context sensitive and therefore able to analyse symbolic forms; and, (4) able to cope with large volumes of data. The above features make content analysis a reasonably appropriate choice, in the current study, for the purpose of analysing large-scale textual data derived from annual reports.

The process of content analysis consists of a number of components. Krippendorf (2004) explains that the first three steps, i.e. *unitizing*, *sampling* and *recording* are somewhat interlinked and form the *data making* sub-process. First, the data have to be distinguished and segmented into distinct analytical units (unitizing); then if there are an unmanageably large number of units, a smaller segment of them has to be selected (sampling); and finally, each unit needs to be coded and described in an analysable format (recording). *Data reduction* is the next logical step which aims to reduce computational efforts. *Inference* is the key step in content analysis and seeks to “consume” all the knowledge a content analyst has about the data and the context. Finally, according to Krippendorf, *analysis* is concerned with “the more conventional

process of identification and representation of patterns that are noteworthy, statistically significant, or otherwise accounting for or descriptive of the content analysis results.” Figure 6 shows the logical connection between the above components.

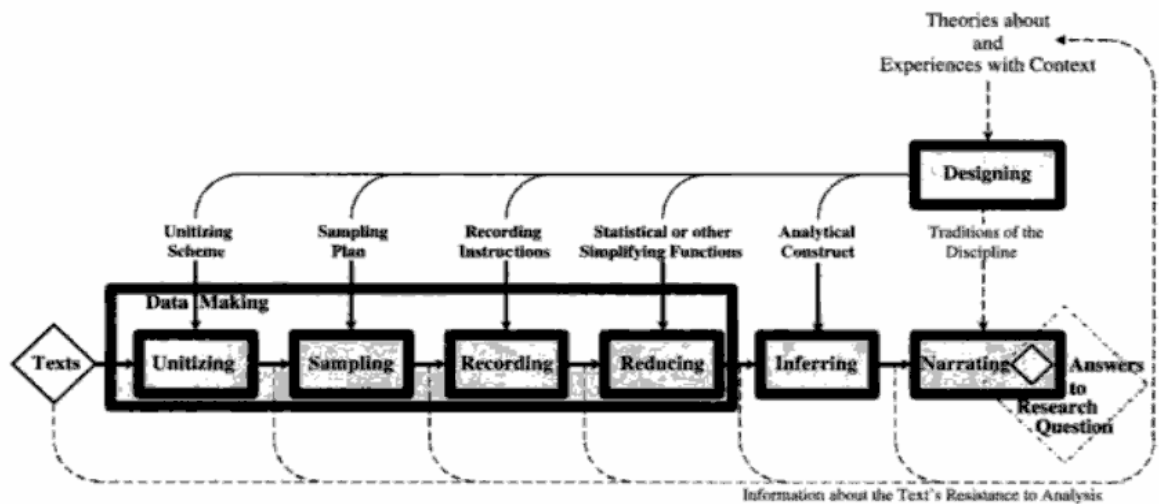


Figure 6: Components of the content analysis process, from Krippendorf (2004)

In chapter 6, I provide a more detailed explanation of the content analysis methodology used in this study.

3.5.2.2 THE CARHART FOUR-FACTOR ANALYSIS

In 1997, Carhart investigated a survivorship-bias free sample of around 1900 equity funds during a relatively long 32-year period. The importance of working with fund data free from survivorship bias is explained by Hendricks *et al* (1997) who demonstrate how studying survivorship-biased data can result in the false discovery of a spurious J-shaped relation between first and second period performances, rather than a monotonically increasing pattern. Carhart classified the funds into categories of long-term growth and growth-and-income, and studied them using both CAPM and his own four-factor model (Fama-French factors plus one-year return momentum).

What Carhart found in his study was that the strong persistence in short-term returns is mostly explained by common factors in the four-factor model, predominantly size and momentum. Consistent with previous studies, he also found that the persistence of underperformance by funds in the bottom decile cannot be explained by the common four factors and fund expenses.

Instead, Carhart finds a strong positive (negative) relation between the previous one-year momentum and the returns on the best (worst) performing decile of funds. His findings suggest that the portfolios of the best funds are tilted towards past winning stocks, and consequently capture their premium. In a similar way, funds belonging to the top decile tilt their portfolios such that they capture the premium on small stocks. Development of multi-factor models such as Carhart's model helped explain, among other things, the various style-timing activities that exist in addition to market timing, namely: size timing, growth timing, and momentum timing.¹⁸

I aim to expand the Carhart model by adding a number of independent variables proxying for fund manager psychological features to the right side of the model. Specifically, I add the overconfidence measure as an independent variable to the model, as displayed in the equation below:

$$E(R_{it}) - R_{ft} = \beta_0 + \beta_{1i}[E(R_{mt}) - R_{ft}] + \beta_{2i}E(\text{SMB}_t) + \beta_{3i}E(\text{HML}_t) + \beta_{4i}E(\text{MOM}_t) \\ + \beta_{5i}\text{OPTIMISM}_{it} + \beta_{6i}\text{CERTAINTY}_{it} + \beta_{7i}\text{SELF-REFERENCE}_{it}$$

I then regress the funds' average monthly returns subsequent to the publication of the annual reports on the Carhart factors and my new overconfidence measure which is based on content analysis of fund manager commentaries. The analysis in Chapter 7 shows that this addition improves, on average, the ability of the model to anticipate future investment returns. Further technical details concerning this analytical method

¹⁸ Market timing refers to the ability to weigh equity exposures according to one's forecast of future market states. Size timing relates to adjusting the fund's exposure between small-cap and large-cap stocks. Growth timing refers to adjusting exposure along the value-growth continuum. Finally, momentum timing modifies the investment strategy between momentum investing (buying high past-return stocks and selling low past-return stocks) and contrarian investing (doing the opposite).

are explained later in the thesis. The following chapter explains the sources of the data in this study as well as the sample selection procedure and provides a description of the data.

CHAPTER 4 - RESEARCH DATA, SAMPLE SELECTION AND SAMPLE DESCRIPTIONS

4.1 INTRODUCTION

The main purpose of this chapter is to provide a broad description of the data sources, the data collection and sample selection procedures. The essence of this study is to explore the relationship between fund manager overconfidence and the fund's investment performance. Therefore, to be able to draw robust conclusions, I need a large sample of mutual funds performance data, and the equivalent sample of mutual fund annual reports on which I perform the content analysis process discussed in the previous chapter.

This chapter is organised as follows: section 4.2 includes a detailed explanation of the data sources including both annual reports and the performance data for mutual funds. It also includes a discussion of the cross-referencing issues faced in linking the two databases for the purposes of this study. Section 4.3 describes the sample selection procedures used in the study. Section 4.4 provides the required sample description.

4.2 DATA SOURCES

This section provides information about the sources as well as a general outline of the data used in this study.

4.2.1 MUTUAL FUND PERFORMANCE DATA

The source of the mutual fund performance data used in this research is the CRSP Survivor-Bias-Free Mutual Fund Database.¹⁹ This database, widely used in the

¹⁹ This database is provided by CRSP (Center for Research in Security Prices) and is accessible online at http://www.crsp.com/products/mutual_funds.htm as well as through the WRDS (Wharton Research Data Services) platform.

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, as explained in Chapter 3.

According to the CRSP Mutual Fund Database Guide, the database includes a history of each mutual fund’s name, investment style, fee structure, holdings, and asset allocation. It also incorporates monthly total returns, monthly total net assets, monthly/daily net asset values and dividends. Schedules of rear and front load fees, asset class codes, and management company contact information are also provided. All the data items are associated with open-end mutual funds and begin at varying times starting from 1962 depending on availability. The update frequency of the database as well as the distribution lag is quarterly. Figure 7 provides a highlight of the data elements included in the database.

TABLE	NAME	DEFINITION
contact_info	Contact Information	Current and historical contact information
daily_nav	Daily Net Asset Value	Net Asset Value for each trading day
daily_returns	Daily Returns	Returns for each trading day
dividends	Dividends	Fund dividends
front_load_det	Front Load Detail	Details of front load fees
front_load_grp	Front Load Group	Effective dates for front load fees
fund_fees	Fund Fees	Fees associated with each fund
fund_hdr	Fund Header	Most recent identification information for each fund
fund_hdr_hist	Historical Fund Header	Historical identification information for each fund
fund_style	Fund Style	Style attributes for each fund
fund_summary	Fund Summary	Summary data for each fund
holdings	Holdings	Portfolio holding information
holdings_co_info	Holdings Company Information	Information about companies held in portfolios
crsp_portno_map	CRSP PORTNO Map	Map to portfolio for security holdings info
monthly_nav	Monthly Net Asset Value	Net Asset Values as of the last trading day of each month
monthly_returns	Monthly Returns	Monthly holding period returns
monthly_tna	Monthly Total Net Assets	Total Net Assets as of the last trading day of each month
rear_load_det	Rear Load Detail	Details of rear load fees
rear_load_grp	Rear Load Group	Effective dates for rear load fees

Figure 7: Overview of data tables included in the CRSP Mutual Fund Database

In terms of fund types covered, the CRSP Mutual Fund Database contains complete historical information for over 44,888 (17,565 dead and 27,323 live funds) open-end funds, including equity funds, taxable and municipal bond funds, international funds, and money market funds. The focus of the current study is on equity mutual funds.

4.2.2 MUTUAL FUND ANNUAL REPORTS

The mutual fund annual reports used in this study are sourced by 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. The database can be accessed via Internet (web or FTP).

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.

In Chapter 3, it is explained how I developed a computer program to automatically download the mutual fund annual reports filed in Edgar. The annual reports are mostly filed in the HTML format. In preparing these reports for content analysis by the *Diction* software, a number of adjustments had to be made. First, all HTML coding has to be removed from the document. Then, all tables with numerical data and all exhibits are removed from the document, since most of them are included purely due to legal requirements and tend to contain template-based language.

4.2.3 CROSS-REFERENCING BETWEEN DATABASES USED IN THE STUDY

The Edgar database uses a Central Index Key (CIK) to identify each of its filings. CIK is a unique ten-digit number allocated to an individual or company by the SEC to identify the relevant filings across several databases. On the other hand, the CRSP Mutual Fund Database uses a different identifier known as CUSIP²⁰ which stands for the Committee on Uniform Security Identification Procedures, founded in 1964. CUSIP is a 9-character alphanumeric code that identifies any North American security for the purposes of facilitating, clearing and settlement of trades.

While both CIK and CUSIP are each useful identifiers within their own databases, there is not a publicly available matching table between the two systems. This was a big challenge in the way of my data collection. To circumvent this problem, I used a cross-referencing table provided by the S&P CUSIP Services to match each CIK to

²⁰ In fact, the CRSP Mutual Fund Database lists funds by its own proprietary identifier known as the CRSP Fund Number which is relatively easy to match with CUSIP.

the corresponding CUSIP.²¹ The matching is however not one-to-one in many cases such that one CIK may be linked to a number of CUSIPs, and vice versa. In such cases, I used the fund's name in a difficult and time-consuming process to provide the correct matching between the two databases.

4.3 SAMPLE SELECTION

This section provides a description of the sample selection procedure. I explain how samples of mutual funds are formed and what data reduction procedures have been used.

I begin by exploring the Edgar database in 2009 and look for all mutual fund filings made during this year. I systematically search for all mutual fund annual reports filed in the form N-CSR (Certified Shareholder Report of Registered Management Investment Companies).²² 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. I exclude amended disclosures. Therefore, by looking at one full year, I acquire the whole annual set of unique mutual fund reports regardless of whether they correspond to the current or previous fiscal year.

Next, I 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, I select only those CIKs whose corresponding CUSIPs belong to actively-managed equity mutual funds.

I use the CRSP fund information to control for fund manager changes. I limit my 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

²¹ I gratefully acknowledge Prof. Richard Taffler's support in obtaining this data.

²² Mutual funds also file semi-annual reports with SEC in the form N-CSRS which are excluded in this study.

the date the current portfolio manager assumed responsibility for the portfolio. Since my whole sample consists of 2003-2009 annual reports, I initially exclude all funds whose *mgr_dt* variable is larger than 1 January 2006. I repeat this process for those annual reports filed during 2008 which have not been filed in 2009, and add the corresponding distinct mutual funds to the sample. I continue until I cover *all 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, I remove from my sample the annual reports with no substantial fund manager commentary (i.e. less than 200 words). Table 1 illustrates this sample selection procedure.

Table 1: The sample selection procedure for sample A

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

Hence, for the purpose of my panel data analysis, I 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. I call this sample A and use it as my main sample for most of the empirical tests in this thesis.

In order to investigate the effect of a longer fund manager duration on the research variables, I make a similar sample of all actively-managed equity mutual funds that have a unique fund manager and complete returns data in the CRSP database during the whole 2003-09 period. I call this sample B.

Table 2: The sample selection procedure for sample B

Mutual fund annual reports filed in Edgar during 2009		3319
<i>Less amended annual reports (N-CSR/A)</i>	<i>166</i>	
Unique mutual fund annual reports filed in Edgar during 2009		3153
<i>Less annual reports with no corresponding CUSIP match</i>	<i>224</i>	
<i>Less bond funds, money market funds and index funds</i>	<i>380</i>	
Active equity mutual fund annual reports filed in 2009		2549
<i>Less mutual funds missing complete returns data during 2003-09</i>	<i>507</i>	
<i>Less mutual funds with a change of the corresponding fund manager during 2003-09</i>	<i>887</i>	
Active equity mutual funds with unique managers and complete returns data during 2003-09		1155
<i>Less mutual funds with missing or no significant fund manager commentary in the corresponding annual reports</i>	<i>149</i>	
Sample B		1006

Therefore, 1006 unique (actively-managed equity) mutual funds during the whole sample period are found subject to the said conditions. In the next section, I provide descriptions for the above study samples.

4.4 SAMPLE DESCRIPTION

Table 3 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 3: Summary statistics of the sample mutual funds

Average 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.²³ 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, representing the ratio of total investment that shareholders pay for the fund's operating expenses which include 12b-1 fees. **Turnover:** Fund Turnover Ratio defined as the minimum of aggregated sales or aggregated purchases of securities, divided by the average 12-month Total Net Assets of the fund.

<u>Year</u>	<u>Number</u>	<u>Average Return</u> (% per year)	<u>TNA</u> (\$m)	<u>Expense Ratio</u> (% per year)	<u>Turnover</u> (% 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

²³ 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 4 provides basic descriptive statistics on the proxies used for measuring fund manager overconfidence. The scores reported in Table 4 are not normalised. Since, for example, the normal range of the Diction optimism score of a typical narrative based on the Corporate Financial Reports dictionary is between 48.21 and 52.50, the relatively low standard deviations are no cause for concern and should be interpreted within this range. The same observation holds for the certainty and self-reference measures.

Table 4: Summary statistics of overconfidence proxies in this study

This table reports the distribution of selected overconfidence proxies based on the content analysis of fund manager narratives. 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.

Panel A: Optimism scores computed by Diction

Year	No. of funds	Mean	SD	Min	1 st	Med	3 rd	Max
2003	2169	51.31	1.96	47.15	49.44	50.68	52.35	57.41
2004	2201	52.29	2.12	47.37	50.38	51.40	53.63	58.23
2005	2287	52.31	2.18	47.47	50.25	51.68	53.57	59.50
2006	2490	51.26	1.98	46.07	49.18	50.82	52.57	56.90
2007	2355	52.77	1.41	49.64	51.44	52.36	53.59	57.42
2008	2612	52.47	2.11	47.57	50.56	51.58	53.80	58.38
2009	2549	53.01	2.20	47.25	50.69	52.53	54.46	59.28

Panel B: Certainty scores computed by Diction, adjusted according to Demers and Vega (2010)

Year	No. of funds	Mean	SD	Min	1 st	Med	3 rd	Max
2003	2169	47.12	1.16	44.66	46.01	46.75	47.73	50.73
2004	2201	46.99	1.19	44.23	45.92	46.49	47.74	50.32
2005	2287	47.79	1.12	45.30	46.73	47.47	48.44	51.49
2006	2490	48.14	1.50	44.21	46.56	47.81	49.13	52.42
2007	2355	46.95	1.14	44.42	45.87	46.62	47.61	50.71
2008	2612	47.21	1.18	44.47	46.14	46.71	47.95	50.51
2009	2549	46.85	1.33	43.37	45.45	46.56	47.73	50.64

Panel C: Self-reference scores, defined as “number of first person pronouns as a percentage of all words”

Year	No. of funds	Mean	SD	Min	1 st	Med	3 rd	Max
2003	2169	1.16	0.16	0.82	1.01	1.11	1.24	1.66
2004	2201	1.07	0.20	0.61	0.89	0.99	1.20	1.63
2005	2287	1.11	0.10	0.89	1.02	1.08	1.17	1.44
2006	2490	1.36	0.19	0.86	1.16	1.32	1.49	1.90
2007	2355	1.29	0.18	0.89	1.12	1.24	1.39	1.88
2008	2612	1.01	0.20	0.55	0.83	0.93	1.14	1.57
2009	2549	1.19	0.24	0.56	0.94	1.14	1.35	1.87

Panel D: Cross-correlations between the overconfidence proxies

	Optimism	Certainty	Self-reference
Optimism	1.000		
Certainty	0.416	1.000	
Self-reference	0.755	0.488	1.000

In chapter 6, I look at the distribution of the overconfidence scores more closely and plot histograms to demonstrate that there is no significant skewness in what is a relatively normal distribution. In addition, instances of extreme (outlier) fund manager overconfidence appear to be more common than underconfidence. I argue that this may be due to the fact that fund manager selection processes that are in operation in the investment industry including hiring interviews are biased in the favour of overconfident managers. A similar distribution exists for the certainty and self-reference measures as can be seen in panels B and C.

The cross correlation matrix in panel D suggests that while optimism and certainty are somewhat correlated measures, there is a significant correlation between optimism and self-reference. This is consistent with the theoretical expectation, and empirical evidence discussed in Chapter 6, that an optimistic, confident fund manager tends to use the active voice as well as personal pronouns more frequently, thus making her narrative more readable.

The following chapter analyses fund manager commentaries using the “close reading” methodology, and investigates how the self-serving attribution bias often leads to overconfidence as can be understood from fund manager narratives. In addition, by manually coding a random sample of commentaries, different story types embedded in fund manager narratives are identified. Furthermore, connections are established among these stories and the funds’ past investment performance, and the results are used to explain the sense-making process that professional investors employ in their very unique work environment.

CHAPTER 5 – SELF-ATTRIBUTION AND OVERCONFIDENCE VIEWED THROUGH THE LENS OF FUND MANAGER REPORTS

5.1 INTRODUCTION

In this chapter, I examine how the self-serving attribution bias drives overconfidence, and how this effect is manifest through fund manager annual reports to their investors. By analysing fund manager commentaries using the “close reading” methodology and in the spirit of Jameson (2000), I identify different “story types” embedded in fund manager narratives and explain how self-attribution bias and overconfidence is traceable in them. Further, I establish connections among these stories and the funds’ past investment performance, and use the results to explain the sense-making process of professional investors in their very unique work environment.

Professional fund managers work under extreme pressure in a confusing and highly demanding environment. They are expected to outperform other equally able managers and their benchmarks on a consistent basis although being aware all the time, on one level, that this is not really possible. Underlying this task is the enormous complexity and intangibility of the markets in which they operate and where there is ultimately little relationship between the decisions they make and the performance of their funds. In addition, there is great difficulty in deciding whether investment returns are due to skill or luck.

Conventional finance views fund managers in terms of “rational” actors in the marketplace using 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. However, 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 judgement, intuition and “gut feeling”. Added to this are the many imponderables which are outside her control and may largely drive her investment performance. Ultimately, the professional fund 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.

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 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 performing a largely context-free analysis.

In this chapter, I also test the proposition that the way in which fund managers deal with their highly stressful, unpredictable and threatening environment is, as we all do, to construct satisfying narratives, and in particular stories, to help them make

sense of what they are doing. These value-creation stories are, as Holland (2006) explains, an intangible part of the overall corporate financial communications framework which can be applied to investment companies in this research.

5.2 UNCERTAINTY IN FINANCIAL MARKETS AND THE CAREER CONCERNS OF FUND MANAGERS

As mentioned earlier, fund managers operate in a highly competitive, uncertain, complex and stressful environment. They are often in constant fear of being fired if their investment performance, which is largely influenced by factors beyond their control, is deemed unsatisfactory. Hence, the strand of mutual fund literature discussing the career concerns of fund managers in the light of their performance is relevant to the discussion in this chapter. The hazards of mutual fund underperformance are clearly spelled out in many studies, e.g. Khorana (1996) and Lunde, Timmermann and Blake (1999). The latter study lists several reasons explaining why funds are terminated: (1) never reaching critical mass during market capitalization; (2) merging an underperforming fund with a similar, more successful one; (3) merging an underperforming fund with a similar one due to merger of two fund families; (4) closing an underperforming fund to improve overall performance. The authors also report that underperformance is generally associated with a higher hazard rate, and since funds to be terminated have higher average persistence than survivor funds, excluding them from persistence measurements results in lower persistence estimates. In a similar study, Chevalier and Ellison (1999) show that fund manager termination is generically performance-sensitive, and more so for younger managers, which may give them an incentive to avoid unsystematic risk. Goyal and Wahal (2008) find that once fund managers are fired, excess returns are typically indistinguishable from zero, though in some cases positive.

The effect of employment risk on fund manager risk-taking behaviour is further investigated in Kempf, Ruenzi and Thiele (2009). They report that if employment risk is perceived to be more (less) important than compensation incentives, fund managers who have experienced a poor mid-year performance tend to decrease

(increase) risk relative to leading managers. Hence, the balance between the desirability of compensation incentives and the undesirability of employment termination determines fund manager's risk levels. Their results are consistent with the study by Hu, Kale, Pagani and Subramanian (2008) who find a non-monotonic (approximately U-shaped) empirical relation between the fund manager's risk level and her prior performance relative to peers. In this context, it is not surprising that fund managers aggressively seek favourable ratings to improve their "perceived image" and eliminate the threat of being fired. Furthermore, numerous studies have shown that fund ratings can have a significant effect on fund flows, which implies that investors are clearly influenced by fund ratings in making their choice.²⁴ Despite the power of fund ratings to influence asset flows into or out of a mutual fund, their predictive ability is widely debated in the mutual fund literature.²⁵

5.3 SENSE MAKING THROUGH NARRATIVES: THE GENERAL FRAMEWORK

The thesis of this chapter is that fund managers, in their reports to clients, seek to make sense of the uncertain and opaque world in which they operate through a constructed process of sense making using the medium of narrative, and in particular story. In this intricate sense making process, fund managers often interpret investment outcomes in a self-serving way which, I argue, drives their overconfidence.

²⁴ For example, Del Guercio and Tkac (2008) use event-study methodology to examine the effect of Morningstar ratings on a sample of 3388 domestic equity mutual funds over the period 1996-1999, while controlling for other contemporaneous influences. The authors show an initial 5* rating can result in a \$26 million average six-month abnormal flow. They also record significant abnormal flows following rating changes.

²⁵ In particular, most fund rating methodologies seem to suffer from a number of shortcomings compromising their usefulness for any ex-ante analysis. Amenc and Le Sourd (2005) point out a few of these in their comparative analysis of three major rating systems: Standard & Poor's star rating, the Morningstar rating, and the Lipper Leader rating: (1) Ratings do not adequately capture the real risk taken by the manager and the necessity for taking extreme risks; (2) Measurement of performance persistence is not yet a major concern for rating agencies; and (3) The relative category-based ranking of fund performance makes the ratings dependent on the definition of the categories used, and therefore compromises their confidence.

Sense making is an integral part of the fund manager's search for meaning. It is "fundamentally tied to processes of individual identity generation and maintenance" (Brown, Stacey and Nandhakumar, 2008). "Sense making is a search for plausibility and coherence that is reasonable and memorable, which embodies past experience and expectations, and maintains the self while resonating with others. It can be constructed retrospectively, yet used prospectively, and captures thoughts and emotions" (Brown et al., 2008). It renders the subjective tangible. Sense-making is the process by which we mould our own identity in an ambiguous world and "tell" ourselves who we are. It is grounded in our constant struggle to construct our own identities.

As well as seeking to persuade their investors that their funds are being well and competently managed (Jameson, 2000), I suggest that the manner in which fund managers report on their performance is, also, part of the process by which they seek to make sense of the impenetrable world in which they are located. The way fund managers construct the cognitive schema they require to be able to do their job in the face of continued threats and reverses is by constructing narratives. As Brown et al. (2008) point out, narrative "constitutes the basic organising principle of human cognition". Sense making is a narrative process where narrative is "the primary form by which human experience is made meaningful" (Polkinghorne, 1988).

Although many authors use the terms narrative and story synonymously, in line e.g., with Czarniawska (2004), I view "story" here as a sub-genre of narrative. Narratives, broadly defined, are texts, spoken or written, that usually involve a sequence of actions and events in a chronological and generally logically consistent manner. They involve temporal *chains* of interrelated events or actions, undertaken by characters (Gabriel, 2008). Narrative truth is fundamentally different from factual truth but nonetheless *real* in that narratives allow us to make sense of situations. More broadly, in terms of the accepted rather than contested nature of financial markets, market participants also make sense of the environment in which they collectively operate through "jointly negotiated" narratives. Narratives carry the market's "common-sensical stock of knowledge" (Brown et al., 2008).

Gabriel (2000) defines stories as “narratives with plots and characters, generating emotion in narrator and audience.... Story plots entail conflicts, predicaments, trials, coincidences and crises that call for choices, decisions, actions and interactions, whose actual outcomes are often at odds with the characters’ intentions and purposes.” The plot functions to transform a chronicle or sequence of events (a narrative) into a story knitting together the events so that one can recognise a deeper significance of an event in the light of other events (Gabriel, 2008). Stories are powerful devices for managing meaning and thus, potentially, an essential part of the fund manager’s sense making process. Through the medium of story the unexpected can be transformed into the “expectable”, and the fund manager can feel, on one level, the unmanageable future is “manageable”. Interestingly “...the truth of a story lies not in the *facts*, but in the *meaning*. If people believe a story, if the story grips them, whether events actually happened or not is irrelevant” (Gabriel, 2000). The key is its “plausibility” rather than its “accuracy”. Importantly, in stories “unpredictability” does not imply “inexplicability”.

I hypothesise in this chapter that through the use of stories and the broader narratives of group sense-making fund managers are able to engage in the process of identity construction and make sense of their impenetrable work task in terms of their needs for self-esteem and purpose, i.e., who they are. Brown et al. (2008), summarising the literature further, argue more generally that such activities can also be analysed using notions of “impression management” and “attributional egotism” (self-attribution bias). The former refers to the self-presentation behaviours that individuals employ to influence the perceptions that others have of them, and the latter the tendency of individuals to attribute favourable outcomes to their own actions and unfavourable outcomes to external factors.

In this chapter, I provide a very preliminary analysis that seeks to test whether fund managers’ search for meaning in an environment where they are required to be exceptional but over which, ultimately, they have little control, can be explained through their use of story and narrative using the epistemology of close-reading (Amernic and Craig, 2009). I hold the belief that the language fund managers employ in explaining their performance “matters”, since their words are carefully chosen and

often convey strategic intent.²⁶ I highlight the role of stories and narratives in this sense making process and, in the spirit of Tuckett (2011) and Tuckett and Taffler (2011) who report on the results of in-depth interviews with fund managers, describe how fund managers weave reason and emotion together in the reports they write to investors and, implicitly, themselves.

The approach used here complements that of Jameson (2000) who also studies shareholder reports of mutual funds but focuses on the process by which fund managers engage with the readers of their reports and how they seek to manage the way in which the text is experienced. In addition, she studies funds whose total returns are high in absolute terms but low in relative terms. I, however, look at the full range of possibilities in terms of outperformance and underperformance relative to benchmarks *and* in absolute terms, and thereby distinguish four different types of commentaries written by fund managers. Importantly, I am directly concerned with how fund managers appear to be using their narratives not only to convince the reader that their investment in the fund is being appropriately and prudently managed, but particularly as a means of helping them make sense of their task and individual identity construction.

I also explain that the way fund managers describe their investment strategies and related processes *ex post* depends, to a large extent, on their prior investment outcomes, and this is an essential part of how they build their own desired self-image and confirm their beliefs in the rationale of their investment process even when their performance is disappointing. If the investment outcome is perceived as favourable i.e. the fund outperforms the market or its benchmark, the manager takes credit for her investment strategies and (consciously or unconsciously) seeks to portray herself as the hero(ine) of the investment story. However, if things go wrong, the manager typically attempts to explain why the strategy is still right but external factors wrong-

²⁶ In their study of CEO-speak, Amernic and Craig (2006) similarly argue that the words managers use “are not chosen in a perfunctory way to report some objective reality. Rather, the words and language are powerful and seductive rhetorical implements for fashioning outlook and opinion.”

footed the underlying processes, and in doing so she depicts herself often as the unfair or undeserving victim of a tragedy type investment story.

5.4 NARRATIVES WRITTEN BY FUND MANAGERS: LOCATING ATTRIBUTION AND OVERCONFIDENCE

Stories are important elements of sense making in organizations, among internal and external stakeholders. As Boje (1991) points out, “people engage in a dynamic process of incremental refinement of their stories of new events as well as on-going reinterpretations of culturally sacred story lines.” He also explains that the storytelling activity is sometimes political since “part of the collective processing involves telling different versions of stories to different audiences.”

I make my entry into the rich literature of organizational storytelling by focussing on a generic framework for studying organizational narratives. This framework investigates three types of narrative coherence, namely, (1) argumentative-structural coherence which relates to the internal logic of the story being told, (2) material coherence which corresponds to the inclusion of all facts and counterarguments, and (3) characterological coherence which is concerned with the believability of the authors or the narrators. Shortcomings associated with either type of coherence may be a sign of bad writing or mental duress, but can also be interpreted in the context of impression management and/or self-serving attribution bias.

From another perspective, Gabriel (2000) studies narratives by focussing on their literary implements through differentiating rhetorical from poetic implements (or tropes). Under rhetorical implements, Gabriel lists metaphors, metonymies, synecdoches, and ironies, while under poetic implements; the author lists eight types of attribution, namely, attribution of motive, causal connections, responsibility, unity, fixed qualities, emotion, agency, and finally, attribution of providential

significance.²⁷ Gabriel points out that without these poetic implements, “no amount of symbolic, rhetorical, or narrative elaboration can be effective.”

Further studies on close reading of financial and accounting narratives include the methodological recommendations for analysing CEO communication proposed by joint authors Amernic and Craig. For example, Amernic and Craig (2006) explore the metaphors and persuasive language used by a number of well-known business leaders in their book titled *CEO-speak* and show that CEOs are often portrayed as heroes fighting the “wars of business” who are capable of astonishing miracles of financial performance and reinvention. In a methodological paper, Craig and Amernic (2009) recommend that any attempt on close reading CEO narratives should reveal (1) the metaphors used by, (2) the ideology adhered to, (3) the rhetoric implemented by the CEO as well as any (4) critical ‘silences’, (5) dichotomies and (6) false distinctions made by the executives. Amernic, Craig and Tourish (2010) add to this list (7) the CEO’s mindset and (8) her attitude to risk exposure and risk management.

While it can be argued that close reading of fund manager narratives should be similar to investigating CEO communication, some distinctions need to be highlighted. Understanding these differences is helpful in comparing and contrasting the results of academic studies on these two related sets of textual data.

Firstly, it is important to recognize that fund managers operate in one industry, the investment industry, whereas corporate executives operate in different industry sectors. Thus, compared to CEOs, one expects to find more homogeneity in the core stories, rhetorical dimensions, and the lexis used by fund managers in their narratives. This feature lends more validity to inter-sample comparisons of fund manager commentaries.

²⁷ *Metaphor* is a figure of speech in which an expression is used to refer to something that it does not literally denote in order to suggest a similarity. *Metonymy* is a figure of speech used in rhetoric in which a thing or concept is not called by its own name, but by the name of something intimately associated with that thing or concept. *Synecdoche* is a figure of speech by which a part of a thing is put for the whole, the whole for a part, the species for the genus, the genus for the species, or the name of the material for the thing made, and similar. *Irony* is a rhetorical device in which there is a sharp incongruity or discordance that goes beyond the simple and evident intention of words or actions.

Secondly, fund managers typically invest in a wide range of securities in many different sectors, each with their own distinct features, resulting in a range of potentially different investment sub-stories. Therefore, arguably, the fund manager may be better positioned, compared to a corporate executive, to be able to engage in constructing a complex meta-narrative of several dimensions when reporting investment outcomes, and better equipped to make rationalizations, find scapegoats and engage in false attributions and dichotomies in case of poor performance. By engaging in this type of storytelling, the narrator can indeed represent accidental actions and events as necessary, thereby overestimating what Goffman (1974) describes as the “causal fabric of experience.”

5.5 STRUCTURE OF THE NARRATIVE DATA USED IN THIS STUDY

I draw my evidence to support the above hypotheses from a pool of fund manager commentaries sourced from the SEC Edgar database. My data includes mutual fund annual reports filed with SEC since 2003, the starting year for such mandatory disclosures. There are on average around 3000 mutual fund annual reports filed in each of the sample years. I select a 2% random sample of these funds for further manual analysis, excluding passive funds. Hence, the fund manager commentaries that drive my anecdotal evidence consist of 60 actively-managed US equity mutual funds.

The body of mutual fund annual reports filed in SEC Edgar typically consists of several sections, among which only the president’s letter and fund commentaries by individual fund managers contain non-quantitative information useful for the purposes of this study. Often, the president and the fund manager narrate different but complementary chapters of the investment story, which demonstrates the concept of contrasting narrators (Jameson, 2000). Since the individual fund managers are often solely responsible for making investment decisions, I believe the fund manager commentaries, compared to the president’s letter, are likely to provide more traction in understanding any relation between the manager’s state of mind and past or future performance. Although the president’s letter can provide investors with a useful big

picture of the investment company's present circumstances, it is often too broad to be helpful for my study purposes. In contrast, the fund manager commentary is an information-rich section of the annual report which helps explain the past performance of the fund and portray its likely short-term and long-term future performance.

Fund manager commentaries often include sections on investment strategy, market environment, discussion of past performance and the fund outlook. Although these sections of the commentary often follow each other to form a single narrative, sometimes, particularly in the face of underperformance, fund managers choose the sub-genre of question and answer to communicate to investors. In this format, the manager answers questions on a variety of issues often covering the above sections, which are then transcribed to form the commentary. An important feature of this narrative structure is the reduced distance between the narrator and the reader. As Jameson (2000) explains, the question-and answer sub-genre invites the reader to imagine himself or herself as the interviewer posing the questions to the narrator, and also permits the narrator to use a more informal tone of voice. Therefore, employing this sub-genre leads the reader to empathize with the narrator and possibly discount the subpar performance.

It is important to emphasize that not all fund manager commentaries contain stories; rather some are purely factual and mostly concerned with performance figures in a narrative format. This may not be surprising given the fact that the funds have to file these official disclosures with the SEC. I, as in Gabriel (2000), distinguish between descriptions that deal with facts-as-information, and stories that deal with facts-as-experience for both narrators and listeners. While in the former, the chronicler is committed to accuracy, in the latter, the storyteller is committed to effect.

5.6 WHAT DO FUND NARRATIVES REVEAL ABOUT THE MANAGERS' STATE OF MIND AND OVERCONFIDENCE: A CLOSE-READING APPROACH

Combining the notion of narrative coherence with the close reading procedure recommended by Craig and Amernic (2009), I propose that critical reading of fund manager communication should involve a search for the following themes:

1. Contextualization of the narrative: fund characteristics, performance history, overall market conditions
2. Narrative's structural-argumentative coherence: attribution of causality, evidence of self-serving attribution
3. Narrative's material coherence: critical silences, dichotomies and false distinctions
4. Mindset and ideology of the narrator: attitude to risk and uncertainty, metaphors employed

The above themes may be more effectively explored when looked at in conjunction with the generic story types (or poetic modes) proposed by Gabriel (2000), i.e. Epic, Tragic, Comic and Romantic. Of these four, the epic and tragic modes adequately represent most of the stories fund managers narrate in my sample. The characteristics of each of these poetic modes are displayed in Table 5.

Table 5: Two unifying story themes extracted from Gabriel (2000)

	Epic	Tragic
Protagonist	Hero	Non-deserving victim
Other characters	Rescue object, assistant, villain	Villain, supportive helper
Plot focus	Achievement, noble victory, success	Undeserved misfortune, trauma
Predicament	Contest, challenge, trial, test, mission, quest, sacrifice	Crime, accident, insult, injury, loss, mistake, repetition, misrecognition
Poetic Tropes	<ol style="list-style-type: none"> 1. Agency 2. Motive 3. Credit 4. Fixed qualities (nobility, courage, loyalty, selflessness, honour, ambition) 	<ol style="list-style-type: none"> 1. Malevolent fate 2. Blame 3. Unity 4. Motive (to the villain) 5. Fixed qualities by juxtaposition
Emotions	Pride, admiration, nostalgia, (envy)	Sorrow, pity, fear, anger, pathos

Hence, I suggest a standard close reading procedure which provides the link between the fund's prior performance and the story type used by the fund manager in her commentary. Depending on significant outperformance or underperformance relative to the fund's benchmark and the underlying market conditions, four different scenarios can be explored using the two major themes, i.e. epic and tragic.

5.6.1 THE EPIC UNIFYING THEME

The common feature of narratives with an epic unifying theme is that fund managers writing such commentaries often attempt to attribute positive investment performance to their own investment ability, skill or talent, while ignoring or downplaying the role of favourable conditions in the macro-environment. The fund manager's critical silences can be identified by observing what significant information on external factors conducive to positive performance happen to be either completely "left out" from the investment story or downplayed in terms of importance.

Epic stories are mostly commonly observed among funds that have outperformed their (self-designated) benchmarks in the fiscal year of the annual report. Their narrative features, however, differ slightly depending on the absolute value of fund returns. In my empirical analysis, I have developed two checklists that can be used in close reading these such narratives. The first checklist addresses narratives of funds that have outperformed their benchmarks in a favourable market (hereafter referred to as Type A commentaries) and the second checklist focuses on narratives of funds in an unfavourable market (hereafter referred to as Type B commentaries).

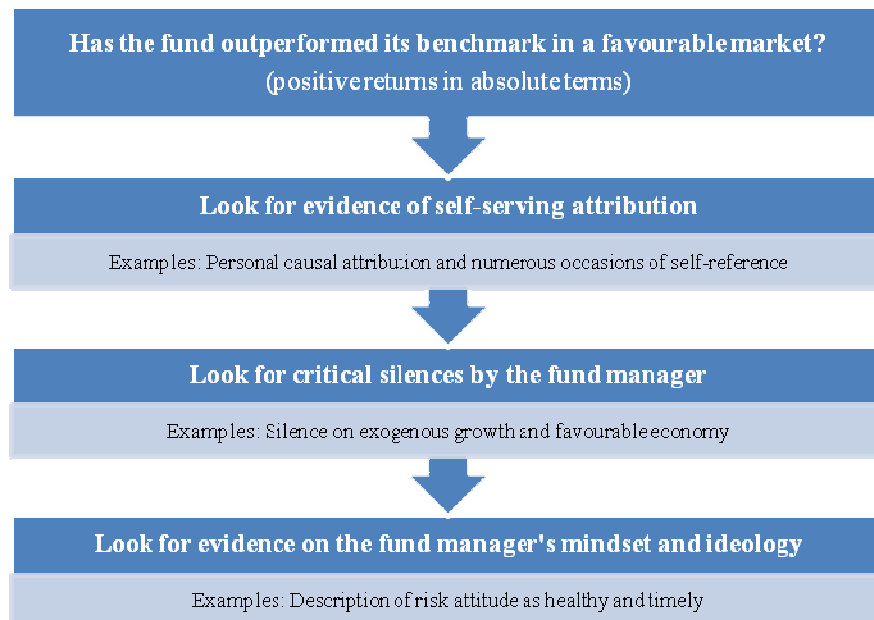


Figure 8: Outperformance in a favourable market (Type A)

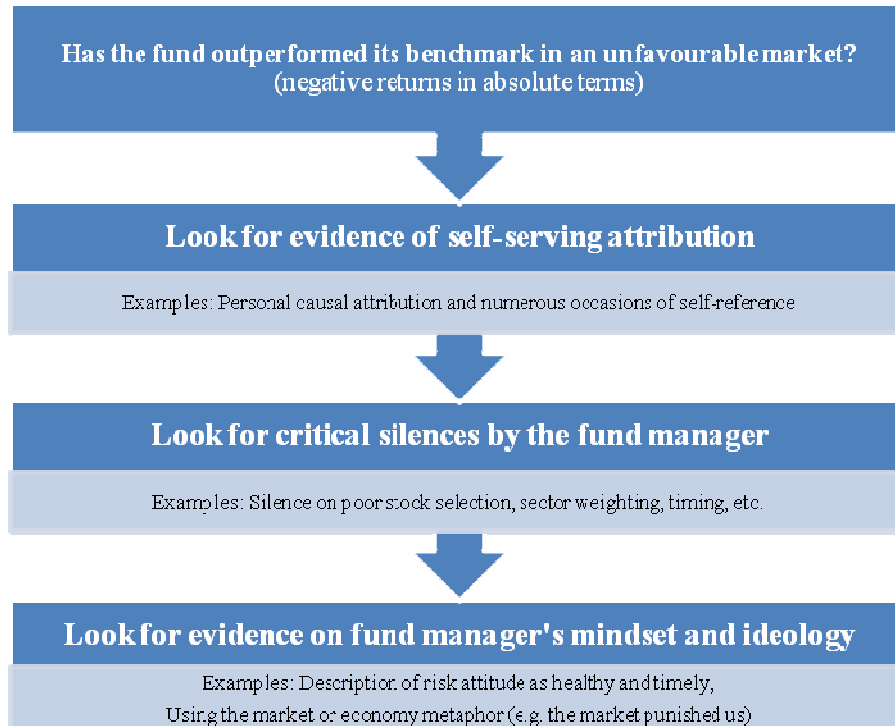


Figure 9: Outperformance in an unfavourable market (Type B)

I now proceed with evidence from a number of fund manager commentaries that represent the epic unifying themes and implement the above checklists. The following example is from a large-cap equity mutual fund that has managed to outperform its benchmark in the year prior to the publication of the report (a Type A commentary):

*Against the fund's benchmark S&P 500's return of 26.46%, Disciplined Equity rewarded investors with a strong 32.50% gain. This was also ahead of its Lipper peer group, as the Lipper Large Cap Core Index rose 28.15%. With our portfolio currently allocated across S&P 500 sectors, the positive results against the S&P 500 and the Lipper Index were **largely a function of our stock selection**,²⁸ as we were able to concentrate the fund in stocks which showed relative strength above their broader sector... **Our** goal is to own the highest quality companies we can in each sector of the market, a judgment made on an array of business metrics that boil down to a combination of attractive valuation and the ability to produce consistent, predictable earnings going forward. In many cases, this means selling a stock and replacing it with another **we** feel has greater potential... The market slump in the first quarter of the year **did trouble us** to some extent [but] the **strength of***

²⁸ Bold fonts are added by the authors to highlight the key points.

our stock picking was evident in our outperformance in all ten S&P 500 sectors... With strong sector by sector performance, **our only weak spots** were a handful of companies that underperformed over our course of ownership.

(Madison Mosaic Disciplined Equity, 2009)

The *protagonist* of this story is the fund's management team (or fund manager) who supposedly delivered superior returns relative to their self-designated benchmark. The story can be characterised as being in the *epic* genre with the protagonist as *hero*. *Inter alia*, the plot revolves around the market slump in the first quarter which constitutes a *challenge* or *trial*, despite which the fund manager is able to outperform her benchmark, or achieve *success* or, implicitly, a *noble victory* through the *agency* of her *ability* and *skill*. What is communicated to the reader is the emotion of *pride* and implicitly an expectation of *admiration* for the *achievement*.

In terms of *causal attributions* and *critical silences*, while I do not wish to imply that the fund manager's description of the factors contributing to the fund's superior performance is deceitful, I point out that no reference whatsoever is made to the generally favourable investment environment of 2009 as demonstrated by an almost uniform rise in S&P 500. Therefore, I conclude that the narrator is exercising *critical silence* on exogenous factors (the first instance). Another *critical silence* by the fund manager is revealed by the choice of benchmarks against which the fund manager measures relative performance. In the 2007 commentary on the same fund, the same fund manager writes:

*We were quite pleased to show a positive return of 9.05% for the period, **nicely ahead of** our S&P 500 benchmark, which was up 5.49%. We slightly trailed our official Lipper peer group, as the Lipper Flexible Portfolio Fund Index advanced 9.57%. However, as we have evolved our fund towards a **more fully invested, all-sector approach, a truer comparison can be made with the Lipper Large-Cap Core Index**, which was up 6.63%. With our portfolio currently allocated across S&P 500 sectors, the positive results against the S&P 500 were **largely a function of our stock selection**, while members of the Lipper Flexible Index may have had greater exposure to higher-returning asset classes, such as government bonds and foreign stocks.*

(Madison Mosaic Disciplined Equity, 2007)

The 2007 commentary above displays the fund manager's *satisfaction* with her performance and implicit expectation of *admiration* in the similar context of the *epic* genre. The fund manager proposes in 2007 that the Lipper Large-cap Core index is the appropriate benchmark for the fund. However, this benchmark is up 39.3% in 2009 and it appears that the manager strategically chooses not to mention this fact (the second instance of *critical silence*).

In addition, while the manager attributes most of the 2007 outperformance to stock-selection, she rules out a similar possibility for members of the Lipper Flexible index, who are supposedly riding "higher-returning asset classes." Also interesting is that the fund manager uses precisely the same attribution phrase to refer to stock-selection in both years which provides anecdotal support for my hypothesis that the writing style employed in the commentary is, to a large extent, a function of performance outcome *ex post*.

In commentaries with an epic unifying theme, fund managers typically end their reports with positive, optimistic remarks. For example, this is how a growth-oriented fund manager described her outlook in 2006, just before experiencing a sharp decline in share prices:

*We believe the Fund's growth holdings have **above-average growth prospects**. It is hard to imagine repeating **the stellar gains** of this fiscal year in the coming year, although we began 2006 with an expected earnings growth rate more than twice that of the S&P 500 Index. The valuation of the overall market appears reasonable after two years in which earnings grew faster than share prices.*

(Jennison 20/20 Focus Fund, 2006)

The following vignette is an example of a fund manager commentary where the fund has lost in absolute terms but still outperformed its benchmark (hence a Type B commentary).

***Even more positive** was our relative performance in the market downturn of the full fiscal year ending June 30, 2009. While declining a significant 18.77%, we provided **a sizable cushion** relative to our performance benchmarks - just at the time when it counted the most (from a risk perspective). The S&P 500 Index declined 26.21% for the fiscal year, and the Lipper Large-Cap Core Funds Index declined 25.69%. Primary reasons for this outperformance were: a) **a slight tailwind by way of company size** on the*

way down, b) significant benefit from our “roughly equal weighted” indexing strategy, which performs particularly well in a precipitous market fall and recovery, c) a flight to “blue chip” quality in the first three quarters of the fiscal year...

(Blue Chip 35 Index Fund, 2009)

In framing this paragraph as an *epic* story, the fund manager starts by emphasizing that the fund has *achieved* to outperform its benchmark, although in the negative domain. While the reader may expect some “matter-of-fact” explanation as to why the fund has experienced negative absolute returns, the fund manager is *critically silent* on this issue. Instead, the reader’s attention is drawn by the fund manager to the “sizable cushion” she has provided against the loss in benchmark.

In terms of *causal attributions*, the use of such vague terms as “a slight tailwind” to convey an external attribution of performance renders the argument ambiguous and borderline meaningless. The description of “the roughly equal weighted indexing strategy” makes it appear as if the manager has some skill in divining the volatility and that it was not a coincidence that the “strategy” succeeded under those market conditions. Their “flight” to blue chip presumably in anticipation of adverse market conditions has the same implication.

The following example is derived from the annual report of a value-oriented fund that has outperformed its benchmarks in 2004 (Type A commentary):

*During the twelve months ended September 30, 2004, Artisan International Value Fund returned 32.81% outperforming both the MSCI EAFE and MSCI EAFE Value Indices. The Fund’s return was **driven by the strength of the team’s security selection** [while] two consumer companies negatively influenced performance during the fiscal year... As we have written on a number of occasions, we are value investors and our sole focus is the purchase of shares in companies that are selling at a meaningful discount to our estimate of economic value. This process is a constant one and does not change based on any prevailing macroeconomic or stock market trend. Over time, we believe our success will be a function of how effectively we value companies, and how disciplined we are at buying them at a discount to fair value, and selling them when they approach fair value... **We invest in companies of all sizes based on valuation and company fundamentals.** We believe that smaller companies outperformed large companies because their valuations were more depressed at the beginning of the year, exactly the reason for their presence in our portfolio.*

(Artisan International Value Fund, 2004)

Here the fund manager embarks on a lengthy discussion of the fund's investing processes and makes the usual personal *attributions of causality* which is a common feature of Type A commentaries. The fund manager proposes that her success is best measured by how well she performs a number of tasks associated with being a portfolio manager. This of course "makes sense" to the fund manager but does not necessarily translate to investment returns for the clients, a point on which she manifests a *critical silence*. It is also interesting how the same fund manager seeks to explain the fund's underperformance relative to benchmark in the following fiscal year:

*The most noticeable aspect of the equity markets during the second and third quarters of 2005 was the **absence of investor conviction**. Trading volumes were low, held down by both the normal **summer trading doldrums** and by the high level of economic and geopolitical uncertainty... The earnings of small companies are **particularly vulnerable to shifts in economic conditions**, and small-cap stock prices have historically reflected this vulnerability. Small caps were strong toward the end of 2004, and they became weak when investor sentiment changed. The July decline of growth stocks was particularly marked in the small-cap market. Despite a September surge by small-cap Internet stocks, the Russell 2500 Index (a broad small-cap index) was still negative at period-end.*

(Artisan International Value Fund, 2005)

The fund manager portrays herself as the *undeserving victim* in the 2005 commentary, by focusing on the numerous *challenges* she has had to face in that year. Lack of investor conviction, the uncertainty in the environment and the "summer trading doldrums" all qualify for implicit *villains* of the story. The stark contrast between the two narratives in explaining the behaviour of small-cap stocks indicates how the fund manager has changed her investment story based on performance relative to the benchmark. I will explore this point in more detail in the following section.

5.6.2 THE TRAGIC UNIFYING THEME

In narratives with a tragic unifying theme, one often observes intricate causal attributions to associate the fund's underperformance with external factors beyond the fund manager's control. The fund manager's critical silences can be identified by observing what significant information on internal factors contributing to poor

relative performance happen to be either completely “left out” from the investment story or downplayed in terms of importance. These often include references to excessive risk-taking or poor stock-selection, sector weighting and timing decisions.

The following is a typical example:

*It has not been an easy year to make money in the market. The war in Iraq, natural disasters, record gasoline and natural resource prices, and fears of inflation, recession, terrorism, etc., have largely offset the positive impact of strong earnings growth resulting in the choppy market we've endured for the past 2 years.*²⁹

(Masters 100 Fund, 2006)

Narratives with a tragic unifying theme are most commonly observed among funds that have underperformed their benchmarks in the fiscal year of the annual report. I study two separate scenarios here similar to the case of outperformance and propose two close reading checklists. First, I have developed the checklist in figure 10 which focuses on narratives of funds that have underperformed their benchmarks in an unfavourable market (hereafter referred to as Type C commentaries).

²⁹ This can be contrasted with very few instances where fund managers appear to take some responsibility for their decisions, albeit cautiously, as in the example below:

*The Fund's higher relative weight in the industrial sector **proved to be a headwind** for performance and lagged the benchmark by approximately 100 basis points. The improvement in GDP during the year, which followed signs of increased industrial activity, did not translate to better stock price performance out of this group... We've either been **wrong or just early** on our industrial sector positioning. We will actively monitor signs of industrial activity and the earnings progress of each company and adjust the portfolio holdings accordingly.*

(Baird LargeCap Fund, 2009)

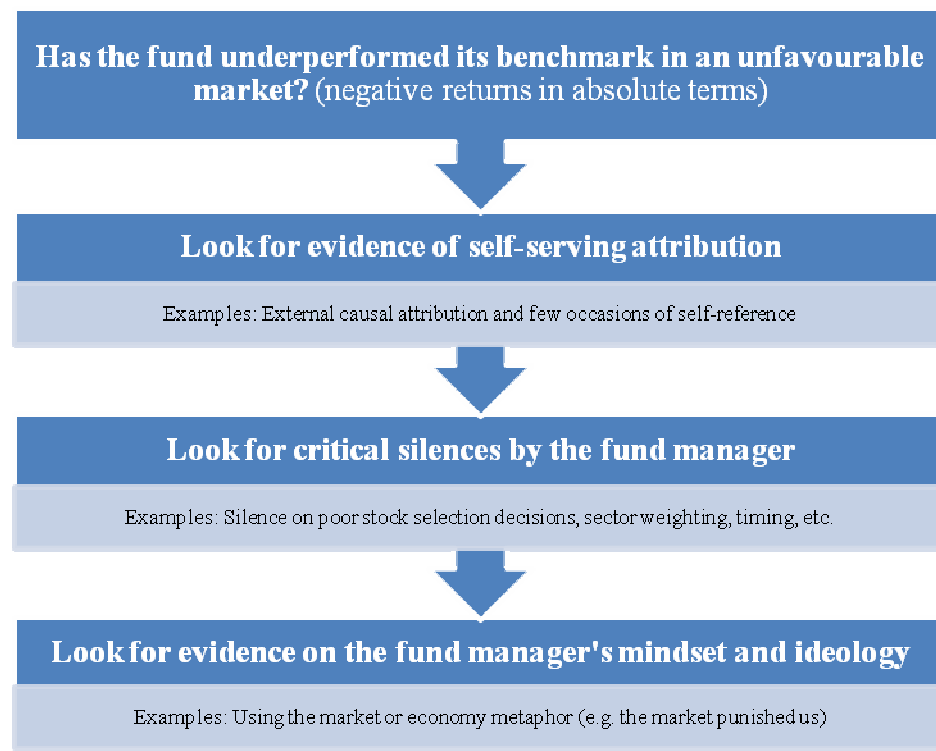


Figure 10: Underperformance in an unfavourable market (Type C)

The checklist in figure 11 focuses on narratives of underperforming funds in a favourable market (hereafter referred to as Type D commentaries). This type of narrative is relatively more complex since returns are ambiguous, among other reasons. Jameson (2000) explains that such narratives typically use a nonlinear structure, contrast narrators to dramatize ideas, embed various sub-genres, and complement verbal with visual discourse such that readers are led to participate in constructing the investment story. I add to this list a number of other observations. Type D commentaries share some elements of epic narratives, since the fund manager often happens to take credit for having delivered positive returns in absolute terms, and does sometimes portray herself as a hero in that context. Hence, as complex as it may sound, this type of commentary may be said to have a tragic-epic unifying theme.

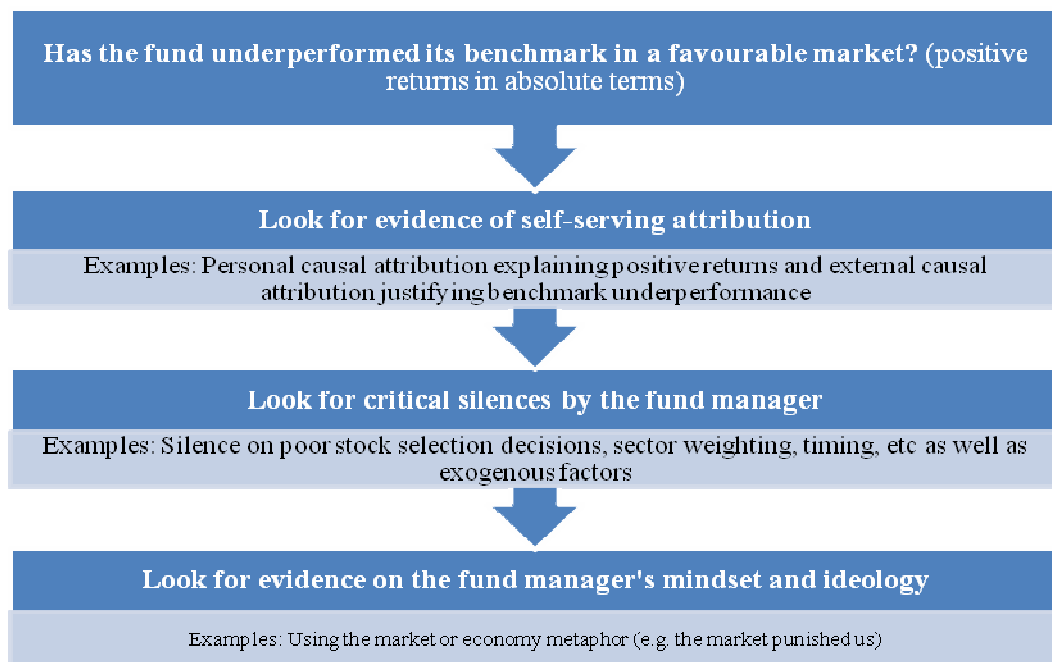


Figure 11: Underperformance in a favourable market (Type D)

Reports with a tragic unifying theme tend to display numerous indirect or implicit mentions of performance detractors. Simple phrases such as “underperformance” or “poor performance” are often replaced by various euphemisms such as: “the fund faced a few clunkers”, “we had only a blemish on performance”, “our stock selection left something to be desired”, “the fund was caught up in some investments we rather like to forget”, “the fund experienced a slight headwind”, “the fund absorbed an opportunity cost”, etc. Using euphemisms, metaphors as well as colloquial (sometimes humorous) phrases in explaining poor performance can be interpreted in the sub-genre of tragic-comic stories, and often serves to confound or obfuscate the underlying bad news. The following is an example:

*Despite a fair amount of interim short-term return volatility, U.S. stock prices “**marked time**” for the ten month period. Equities were buoyed by a number of factors (e.g., low interest rates, relatively constrained inflation, strong housing markets, generally strong corporate profits and balance sheets, continued productivity gains, generally improving labor markets), but also were **buffeted by a variety of concerns** (e.g., the war in Iraq and other geopolitical matters, higher oil prices, **generally subdued capital spending**) that tended to **gain the upper hand in terms of investor sentiment**.*

(Enterprise Capital Appreciation Fund, 2004)

Another common feature of commentaries with a tragic unifying theme is the slow and careful *development of the plot*. As opposed to epic commentaries where the good news of outperformance is immediately broken to the readers, in the tragic scenario the fund manager often sets the scene for the bad news after a long and detailed description of the disastrous environment in which the fund operated and the *predicaments* it faced. The actual bad news can be hidden among plenty of other potentially confusing information, as can be seen in the following example:

Uncertainty in both equity and fixed income markets dominated this year. Volatility, which was slightly bolstered at the end of 2007, soared to unimagined heights through the 3rd quarter of 2008. This environment was due to a confluence of decelerating global growth, energy and commodity price inflation and ongoing credit turmoil. While energy and commodity prices have retracted from speculative levels, credit problems and recessionary pressures persist...

Major U.S. equity indices declined more than 35% for the twelve months ended October 31, 2008. The S&P 500 Total Return Index was down -36.09%, the Russell 3000® Index down -36.60%, the NASDAQ Composite down -39.81%, and international markets fared worse, with the Morgan Stanley Capital International (MSCI) All Country World Index ex U.S. returning -48.53%. By contrast, bond indices were barely positive, with the 12-month return of the Barclays Capital Aggregate Bond Index at 0.30% and the Merrill Lynch U.S. Corporate, Government and Mortgage Index up 0.70%.

*All four Pro-Blend Series continue to outperform over the current stock market cycle with solid absolute returns for long term investors. **However, the one-year performance results versus the market and benchmarks were mixed for the year ended October 31, 2008** with the Pro-Blend Conservative Term Series and the Pro-Blend Maximum Term Series holding up slightly better than their blended benchmarks and the Pro-Blend Moderate Term Series and Extended Term Series underperforming...*

(Pro-Blend Series, 2008)

Notice that only in the third paragraph and after a lengthy discussion of the how different benchmarks indices have performed is something written about the actual funds in question. No matter how negative and sometimes frightening a description fund managers provide of their operating environment in the face of poor performance, they typically end their narrative with a note of optimism or at least no major concern for the future. This is how the same fund manager ended her commentary in the immediately preceding fiscal year:

*While volatility can be difficult to endure, it also provides investment opportunities for those who maintain a disciplined individual security selection process. Our bottom-up process, **focused on longer-term trends**, solid fundamental analysis, and time-tested investment strategies, is well suited to this type of environment.*

(Pro-Blend Series, 2007)

The paragraph below is how a fund manager ended her 2006 commentary. In 2007, however, the fund suffered from a negative performance of -4.52% compared to a 7.72% rise in its benchmark, the S&P 500 index:

*After three years of watching the companies in our portfolio grow earnings at double digit rates, but with little or no return to shareholders, it is refreshing to see the Fund beginning to perform better. In fact, we believe that **we are entering a “catch up” period** where our holdings should outperform both their respective fundamentals and the S&P 500 Index. Because of this, **we look forward to the next year with optimism and continue to appreciate your support of our strategy through your holdings in the Fund.***

(Thompson Plumb Growth Fund, 2006)

In framing her story in the *tragic* genre, the fund manager of the above fund appeals to the emotions of the clients in the hope of maintaining their trust in the fund. The manifestation of *pathos* is a characteristic feature of stories with a tragic unifying theme.

The following narrative is an example of a fund that has outperformed one benchmark and underperformed another. In this example, the fund manager labels the 0.88% outperformance compared to the primary benchmark “quite an accomplishment”, and *blames* the size “headwind” for the lower performance relative to the fund’s peer benchmark.

*For the six months ending June 30, 2009, our Fund appreciated 4.04%, beating our primary market benchmark - **quite an accomplishment** in a market dominated by small- and mid-size stocks - but lagging our peer benchmark. The S&P 500 Index rose 3.16%, and the Lipper Large-Cap Core Funds Index rose 5.35%. Considering we had a **“headwind”** of almost two percentage points due to the size of our holdings versus our primary market benchmark, we are quite pleased.*

(Blue Chip 35 Index Fund, 2009)

The *self-admiration* expressed in this vignette is a characteristic emotion associated with such commentaries. The “sailing” and “flying” *metaphors* employed here are commonly used by fund managers to describe their investment strategies in their commentaries. This may signal an unconscious need on the part of the fund manager to believe in “the ability to control and change direction” in what is essentially a highly unpredictable environment.

The following excerpt is another example of a fund underperforming its benchmark in a favourable market (a Type D commentary). The narrative is interesting due to subtle *critical silences* of the fund manager:

*For the 12 months ended October 31, 2009, the S&P 500 Index finished with a return of 9.80% while the average large-cap blend fund monitored by Morningstar, Inc. recorded an average 11.86% result... In the same 12-month period, John Hancock Sovereign Investors Fund’s Class A shares returned 8.75% at net asset value. During the market’s declining phases, the Fund outperformed its benchmark, as investors were on the defensive and **focused on** the kind of mega-cap, high-quality, dividend-paying **stocks the Fund typically owns**. However, the Fund lost ground versus the benchmark when share prices turned higher and investors adopted a more speculative approach, favoring lower-quality names with smaller capitalizations.*

(Sovereign Investor’s Fund, 2009)

In terms of *causal attributions*, the fund manager starts by focusing on the period during the prior year when the fund was outperforming its benchmark but stops short of attributing this event to their superior stock selection. Rather, she portrays the fund as almost having a mind of its own that chooses to “typically own” certain stocks. This defensive explanation is subsequently used in the next statement to help the fund manager avoid taking responsibility when the market changes to a more speculative mode. Therefore, the *critical silence* by the manager is on the actual reasons leading to the fund’s underperformance, possibly including poor decisions on stock selection, sector weighting, timing, etc.

In seeking to explain underperformance and (consciously or unconsciously) obfuscating bad news, fund managers sometimes draw the readers’ attention to the fund’s performance potentials in the long term, which of course is an ambiguous phrase with no commonly-agreed definition:

*The fiscal year was truly a **tale of two markets**. During the first four months of the fiscal year, equity markets experienced steep declines as severe problems in the credit markets, a rapidly weakening housing market, rising energy and food prices and a deteriorating outlook for corporate earnings led to a global economic recession. However, equity markets rapidly reversed direction beginning in March 2009 and rallied solidly through most of the remaining months in the fiscal year.*

*However, the Fund began to underperform the Russell 1000 Growth Index when equity markets hit a bottom and began to rebound in March 2009. It is important to note that while our investment process **may temporarily underperform** our peers at market inflection points, our goal is to **outperform over a full market cycle**.*

(AIM Large Cap Growth Fund, 2009)

The fund (manager) is again portrayed as the *undeserving victim* in this story, and the *villain* is supposedly the market with all its underlying uncertainty. Although the overall performance of the fund lags its benchmark, the *dichotomy* used by the fund manager to split the fund's performance in two separate sub-narratives aids the reader in discounting the inferior performance. This phenomenon is explained by the mental splitting which occurs when subjects simultaneously analyse two pieces of contradictory information. Similarly, in the following Type D vignette, the fund manager is faced with the problem of justifying underperformance relative to benchmark:

*The financial statements that make up the Annual Report give us an opportunity to review what has happened and gain some insight into what may happen. For the twelve months ending September 30th 2006, the Growth & Income Fund was up 5.40%. This was below the S&P 500 Index which was up 10.79%. **Although the return for the last year was below average, a review of the last three years shows the Growth & Income Fund to be competitive, up an average of 11.26% per year. This compares with the Dow Jones and S&P 500 which had annual average returns of 10.02% and 12.30% respectively over the last three years.***

*It is always a **tug-of-war** in the securities markets with the negative forces of geopolitical events, natural disasters and corporate corruption pushing securities down. This is countered by man's desire to grow, achieve, and innovate. The good news is that in the long run, the positives have prevailed... **Our investment story** has been, and continues to be, that the negatives are more than offset by a strong US economy and record corporate profits. Our optimistic investment outlook goes beyond the US border...*

(Elite Growth & Income Fund, 2006)

The above fund manager avoids having to explain the fund's underperformance by engaging in another *dichotomy*, this time between the fund's prior one-year and the prior three-year record. The *villains* of the story are again the uncontrollable market forces which one can always blame for anything that has gone wrong. The fund manager also employs the "fighting" *metaphor* to stress the role of external factors. In the last paragraph, the fund manager takes on the mantle of a teacher explaining to the reader how securities markets generally operate, prior to ending the narrative with a rather uncalled-for and prophetic note of optimism.

5.7 CONCLUSIONS

In this chapter, by analysing fund manager commentaries using the "close reading" methodology, I demonstrated how self-attribution bias and overconfidence are manifest in these narratives and how the former often drives the latter. By manually coding a random sample of fund manager reports in the spirit of Jameson (2000), I identified different "story types" embedded in fund manager narratives and established connections among these stories and the funds' past investment performance. Finally, I used the results to explain the sense-making process of professional investors in their very unique work environment.

The research results help explain how fund managers often engage in telling "stories" to their clients in order to help construct their identity, justify their added value and cope with the enormous pressures of a highly unpredictable and stressful working environment. A common set of unifying themes i.e. epic and tragic, as well as a number of sub-themes, motivate the stories that fund managers essentially narrate in their commentaries. Fund managers adjust, both consciously and unconsciously, the theme of the investment story, elements of the plot, critical silences, the tone of voice used, the readability of their narratives, the level of obfuscation and other narrative features *ex post* depending on their investment outcomes. In this way, the stories and meta-narratives embedded in fund

commentaries help fund managers explain what they do, both to themselves and to their clients, and maintain conviction in their performance and processes against the backdrop of a very uncertain workplace.

6.1 INTRODUCTION

In this chapter, I empirically investigate how past investment results influence fund manager report tone and readability which are closely associated with fund manager overconfidence. I focus on the way fund managers set out to communicate financial performance to their clients and potentially engage in impression management. Unlike the previous chapter which employed a close-reading methodology, this chapter adopts a corpus-linguistic approach facilitated by large-scale computer-assisted analysis of textual data. By studying the corpus-linguistic features of fund manager reports, I demonstrate how different groups of fund managers develop the core message in their narratives in very different way (i.e. genres) in light of past performance.

This chapter also explores how my selected overconfidence proxies (which I have derived directly from DICTION) are affected by prior investment performance. This step sets the scene for the following chapter which investigates the potential impact of overconfidence on subsequent investment returns. Hence, I test the following two null hypotheses in this chapter:

- There is no significant difference in the *tone/readability* of fund manager commentaries whose corresponding funds have experienced varying degrees of past investment performance, *ceteris paribus*.
- There is no significant difference in the *optimism/certainty/self-reference* attributes of fund managers whose corresponding funds have experienced varying levels of prior investment performance, *ceteris paribus*.

I start this chapter by presenting, in section 6.2, some evidence on the systematic study of annual reports in the area of accounting and finance. Section 6.3 explores the fund manager commentaries in the sample from the perspective of the genre analysis investigates the effect of prior performance on the tone taken by the fund

manager. Section 6.4 focuses on the readability of the commentaries in light of different prior performance outcomes. Section 6.5 investigates the effect of past returns on optimism, certainty and self-reference (overconfidence proxies) across fund manager reports. Finally, section 6.6 summarises and concludes the chapter.

6.2 SYSTEMATIC STUDY OF FINANCE AND ACCOUNTING NARRATIVES

The importance of studying finance and accounting narratives is illustrated by the growing emphasis on the objectivity of accounting literature as a means of communicating financial performance. The narratives dealt with in this research, including commentaries on evaluation of past performance, justifying present investment circumstances and expressing opinion on the investment outlook, merit close attention as they all are, according to Gabriel (2000), essential parts of the organizational sense-making process among various stakeholders.

The annual report is the main medium used in the current study to research narratives prepared by professional investment houses. In terms of structure and intended purpose, investment company annual reports are reasonably comparable to corporate annual reports produced and filed as formal public documents by large companies in most western economies. Stanton and Stanton (2002) cite a study which demonstrates that corporate annual reports have become “a highly sophisticated product of the corporate design environment, the main purpose of which is to proactively construct a particular visibility and meaning rather than revealing what was there.” This is consistent with the inherent reflexivity of language, i.e. language both mirrors and constructs (construes) reality in a desired way Fairclough and Holes (1995). In other words, as Hines (1988) suggests, people create a picture of an organization, they think and act on the basis of that picture, and “by responding to that picture of reality, they make it so.”

There exists a substantial body of literature examining corporate annual reports from various perspectives. Researchers often investigate sections of, or even the whole annual report and focus on themes such as impression (image) management, marketing, organizational legitimacy, political economy, accountability, etc. Stanton

and Stanton (2002) provide a comprehensive review of this vast literature by categorizing 70 of the most important “useable studies” in the field. The focus of these studies has been extremely wide, with no one particular area dominating the attention of the cited authors.

The annual report studies that investigate narratives and stories appear to agree on a number of shared patterns: the way a story is told by the narrator, as well as what the story says, both matter. Linguistic theory provides “a range of language choices and constructions that report preparers can use to pursue their goals without misinformation or complex language” (Stanton and Stanton, 2002) and, as such, the choice of verb structures, themes, subjects, context, cohesion and condensations all determine meaning, as Thomas (1997) explains. Just as importantly, narrative theories discuss different sets of factors that influence meaning, (Stanton and Stanton, 2002). These include the sources of meaning, the narrative structure, the reader interaction with the text, the existence of different narrators and different genres (modes of narration e.g. epistles, lessons, sermons, essays and question-and-answer dialogues). In addition, the coherence of the narrative is highly relevant to this discussion. Ihlen (2002) explains three types of narrative coherence, namely, (1) *argumentative-structural* coherence which relates to the internal logic of the story being told, (2) *material* coherence which corresponds to the inclusion of all facts and counterarguments, and (3) *characterological* coherence which is concerned with the believability of the authors or narrators.

Prior research also seems to agree on the fact that language is often used to obfuscate the bad news and thus blur distinctions on the causes of poor performance. Courtis (2004) defines obfuscation as “a narrative writing technique that obscures the intended message, or confuses, distracts or perplexes readers, leaving them bewildered or muddled.” Narrators often achieve this effect through “the use of esoteric or obscurantist vocabulary and/or gobbledygook, extraneous and non-relevant information, long sentences with complex grammatical structures and/or high variability in reading ease, and convoluted and/or spurious argumentation.”

More streamlined studies on financial and accounting narratives include the methodology recommended for analysing CEO communication by Craig, Garrot and

Amernic (2001) and Amernic, Craig and Tourish (2010). The former study states that any attempt at “close reading” CEO narratives should reveal (1) the metaphors used by, (2) the ideology adhered to, and (3) the rhetoric implemented by the CEO as well as any (4) critical ‘silences’, (5) dichotomies and (6) false distinctions made by the executive. The latter study add to this list (7) the CEO’s mindset and (8) the CEO’s attitude to risk exposure and risk management.

In brief, the broad spectrum of perspectives used to investigate annual reports can be understood in the light of managerial incentives and the audience of these reports. Stanton and Stanton (2002) aptly summarize this point:

“Whether an annual report is written from the perspective of seeking to reduce the effects of events perceived to be unfavourable to a corporation’s image, or as a proactive document seeking outcomes that advance the corporation’s or management’s objectives, reflects a division between the pursuit of legitimacy and corporate social responsibility on the one hand, and political economy, image management and marketing interpretations on the other. Accordingly, preparers presumably select and organise their material in terms of the kind of audience they seek to address.”

In either case, managers are equipped with an increasingly “complex arsenal of communication tools” including selection and integration of narratives, language, images, graphs etc. to create, what Jameson (2000) calls, a hyperstructure that effectively engages the audience as part of the story. Finally, it is important not to forget that the narrator is a hidden audience to her own story.

6.3 ANALYSING GENRE AND TONE OF FUND MANAGER COMMENTARIES IN LIGHT OF PAST INVESTMENT PERFORMANCE

This section investigates mutual fund annual reports from the perspective of genre theory. The notion of genre is grounded in organizational communications. Miller (1984) defines genre as “typified rhetorical actions based in recurrent situations.” Genres exist at different levels of abstraction, and can be identified in very broad as well as very specific contexts. For instance, Rutherford (2005) identifies the narrative

section of UK corporate annual reports (also known as the Operating and Financial Review or OFR) as a middle-range genre of corporate communications between organizations and their stakeholders. In a similar way, I argue in this section that the commentary provided by the mutual fund manager can be treated as an impactful genre of corporate communication between the fund manager and the investors with its own distinct sub-genres. I use *word-frequency analysis* to demonstrate which sub-genres exist in fund manager narratives and discuss their links to past and expected future investment performance.

Word-frequency analysis is part of an increasingly versatile and modern methodological toolbox in corpus linguistics. As an empirical methodology, corpus linguistics seeks to analyse actual patterns of language use by employing a large, systematically organized body of texts known as the corpus (Rutherford, 2005). It can be used in textual analysis to distinguish between different genres, as well as explore features of individual genres. In the context of this research, word-frequency analysis is primarily used to identify the different sub-genres used in the fund manager's communication of performance results.

The sample used in this chapter consists of all actively-managed equity mutual funds with unique managers and complete returns data during 2003-09 that have significant fund manager commentaries in their annual reports. This corresponds to sample B in chapter 4 which comprises 1006 funds in total and, correspondingly, 1006 fund manager commentaries for each of the seven years from 2003 to 2009. The average length of each fund manager commentary is 692 words (about two pages). Therefore, on average, the whole corpus under study consists of around 700,000 words for each year.

I look at the trend of certain corpus-linguistic features of fund manager commentaries throughout this period, and, in particular, focus on 2006 and 2008. The reason for selecting these two years is that they are, to a large extent, polar opposite snapshots of the overall economic environment of the mutual fund industry, as proxied by leading market indices (see Appendix 5). In other words, while 2006 is a sufficiently good proxy for a bullish year with regards to the US and global financial markets, 2008 can be treated as a bearish year in the same context.

Based on the fund's broad investment style reported in the CRSP database and denoted by the fund's *Lipper Objective Code*, I subdivide the sample funds into two categories of *Value-oriented* and *Growth-oriented* funds. Value-oriented funds (also known as Income-oriented funds) normally seek a high level of current income through investing in income-producing stocks, bonds, and money market instruments, and they consist of 277 funds in my sample. Growth-oriented funds normally invest in companies with long-term earnings expected to grow significantly faster than the earnings of the stocks represented in the major unmanaged stock indices. My sample includes 382 funds in this category. I delete those funds whose objective codes change during 2003 and 2009 (around 8% of the sample).

I also divide the funds, based on prior-year absolute annual returns into *loss-making* (negative return), *least-profitable* (bottom decile positive return) and *most profitable* (top decile positive return) categories. The number of funds in each category changes during the sample years. Finally, I divide the funds based on size (total net assets) into the *smallest* (bottom decile) and *largest* (top decile) categories. Hence, I end up with seven categories for the purpose of corpus-linguistic analysis.

The first stage of the analysis explores the frequency of eligible words across all the sample annual reports. Similar to the methodology used by Rutherford (2005), the following word groups are excluded from the analysis in order to make a list of eligible words: (1) frequently occurring grammatical elements such as articles, conjunctions, pronouns, and common verbs; (2) days, months and years; (3) numbers, including monetary amounts, in words, figures and denominations. Rutherford also manually removes specific company and product names, but this is clearly not feasible in my much larger sample. However, these specific words should not introduce any significant bias in my analysis as they often include the name of the fund discussed in each commentary and therefore, in aggregate, are not expected to appear among high-frequency words.

The word-frequency analysis is performed using the *Concordance* software. *Concordance* is a powerful program which is primarily used, as its name suggests, to provide many different types of comprehensive and selective concordancing

functions. Importantly, *Concordance* is capable of analyzing text files with unlimited length.

Table 6 lists the average 50 most frequently used eligible words across the sampled commentaries. I have merged all the fund manager commentaries to arrive at a single master corpus document for each year. Then, I have used *Concordance* to calculate the highest-frequency words in each year and then averaged the results across the years.

Table 6: Highest frequency eligible words used across fund manager commentaries in an average sample year

<u>Instances</u>	<u>Frequency</u>	<u>Word</u>	<u>Instances</u>	<u>Frequency</u>	<u>Word</u>
11312	1.63%	Fund	2113	0.30%	Holdings
9323	1.34%	We	1989	0.29%	Opportunities
7086	1.02%	Year	1865	0.27%	Current
5967	0.86%	Market	1865	0.27%	Information
5594	0.80%	Performance	1740	0.25%	Fiscal
4973	0.71%	Funds	1740	0.25%	Fund's
4973	0.71%	Growth	1740	0.25%	Industry
3605	0.52%	Investment	1740	0.25%	Long-term
3232	0.46%	Interest	1740	0.25%	Positive
3232	0.46%	Stock	1616	0.23%	Inflation
3108	0.45%	Index	1616	0.23%	Period
3108	0.45%	Sector	1492	0.21%	Economic
3108	0.45%	Stocks	1492	0.21%	Profit(s)
2984	0.43%	Companies	1492	0.21%	New
2984	0.43%	Consumer	1492	0.21%	Returns
2984	0.43%	Economy	1492	0.21%	Return
2859	0.41%	Strong	1492	0.21%	Services
2859	0.41%	Years	1367	0.20%	Products
2735	0.39%	S&P	1367	0.20%	Returned
2735	0.39%	Technology	1367	0.20%	Shareholder
2611	0.38%	Prices	1304	0.19%	Loss(es)
2362	0.34%	Past	1243	0.18%	Because
2362	0.34%	Portfolio	1243	0.18%	Business
2362	0.34%	Value	1243	0.18%	Data
2238	0.32%	Believe	1243	0.18%	Earnings
2238	0.32%	Higher	1243	0.18%	Lower

The word “fund” is the most frequently used word in the corpus closely followed by the pronoun “we”. This is an interesting observation as the higher occurrence of the latter relative to the former may be an alternative proxy for self-reference and possibly even fund manager narcissism. Therefore, I define a simple “narcissism” ratio by dividing the number of “we” instances by the number of “fund” instances for each narrative. For the whole sample, this “narcissism” ratio is equal to 0.824.³⁰ Higher values of the ratio (particularly more than 1.016 which is one standard deviation larger than its mean) can signal fund manager narcissistic tendencies. As expected, this ratio is highly correlated (0.831) with my standard self-reference measure which looks at the frequency of all first-person singular and plural pronouns.

Figure 12 shows the word length chart of the average fund manager commentary in the corpus. The average word length is 6.8 characters and four-character long words are the most frequently used in the narratives. I will revisit this statistic in a longitudinal study to explore the dynamic readability and verbosity of fund manager commentaries.

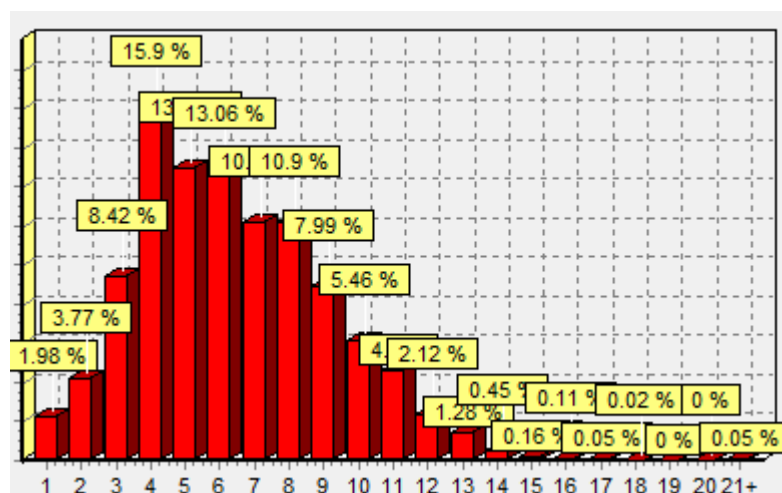


Figure 12: Word length chart of the average fund manager commentary

³⁰ The researcher has observed that fund managers often tend to refer to their own fund under management in singular format and the competition or the industry in plural. Hence, instances of the word “funds” are not considered in calculating the “narcissism” ratio.

Next, I investigate the linguistic features of the fund manager commentaries through the sample years. It is important to bear in mind that the mutual fund industry experienced two rather distinct economic macro-environments during the sample period, i.e. the “bullish” years of 2003-2006 and the “bearish”, volatile years of 2007-2009. In this context, it is interesting to observe the impact of these external environmental factors on the lexical features of fund manager reports. Table 7 demonstrates a number of these measures and also lists the 10 most frequently used words in the commentaries each year.

Table 7: Corpus-linguistic features of fund manager commentaries through the sample years

	<u>2003</u>	<u>2004</u>	<u>2005</u>	<u>2006</u>	<u>2007</u>	<u>2008</u>	<u>2009</u>
Total words (“tokens”)	594	552	636	679	729	795	860
Distinct words (“types”)	2049	1833	2232	2370	2223	2202	2511
Type-token ratio	3.45	3.32	3.51	3.49	3.05	2.77	2.92
Words per sentence	9.8	10.2	9.5	11.0	12.4	13.9	13.5
Characters per word	5.7	6.4	6.1	7.0	6.9	7.9	7.6
10 highest-frequency words	We	We	We	Fund	Fund	Fund	Fund
	Fund	Fund	Fund	We	We	We	We
	Performance	Growth	Performance	Year	Market	Year	Market
	Growth	Investment	Strong	Performance	Index	Market	Year
	Year	Performance	Growth	Strong	Economy	Index	Economy
	Stock	Strong	Investment	Growth	Investment	Economy	Funds
	Strong	Stocks	Believe	Funds	Because	Sector	Index
	Believe	Market	Market	Higher	Performance	Value	Investment
	Higher	Funds	Economy	Stock	Value	Because	Interest
	Interest	Index	Stock	Market	Funds	Investment	Stock

A number of interesting observations can be made by looking at Table 7. During the “bullish” years, with the exception of 2006, fund managers more frequently refer to themselves by mentioning “we” rather than the “fund”, while the reverse pattern emerges during the “bearish” years. The difference in word frequencies is significant at the 5% level using the t-test with unequal variance.

Similarly, fund managers appear to write more frequently about their often “strong” record of “performance” or “growth” during the pre-2007 years. On the contrary, during the 2007-2009 period, fund managers make more frequent citations of the “market” as well as the “economy”, possibly for the self-serving purpose of projecting relatively less glorious performance on environmental externalities.

The word “because” makes two interesting appearances in the 10 highest-frequency words in 2007 and 2008. This can possibly be attributed to the fund manager’s preference to “talk herself out” of explaining an undesirable investment outcomes by advancing more causal arguments.³¹ The word “index” is also cited more frequently during the “bearish” years, for the likely reason of making relative performance comparisons.

Figure 13 shows a plot of the linguistic variables reported in Table 7 across the sample years. Apart from a rather steady rise in the average length of the fund manager commentaries across the sample years, the narratives in the post-2007 years appear to have, on average, longer sentences composed of longer words. In addition, the *type-token ratio* (ratio of distinct words to total words) is relatively lower during the “bearish” years, which, together with the above patterns, seem to suggest that fund managers write longer, more verbose and less readable commentaries when communicating less desirable performance results.

³¹ Li (2008) demonstrates that a higher frequency of causation words (such as “because”) in the Management Discussion and Analysis of corporate annual reports is associated with less persistent earnings. I do not attempt to test a parallel hypothesis here.

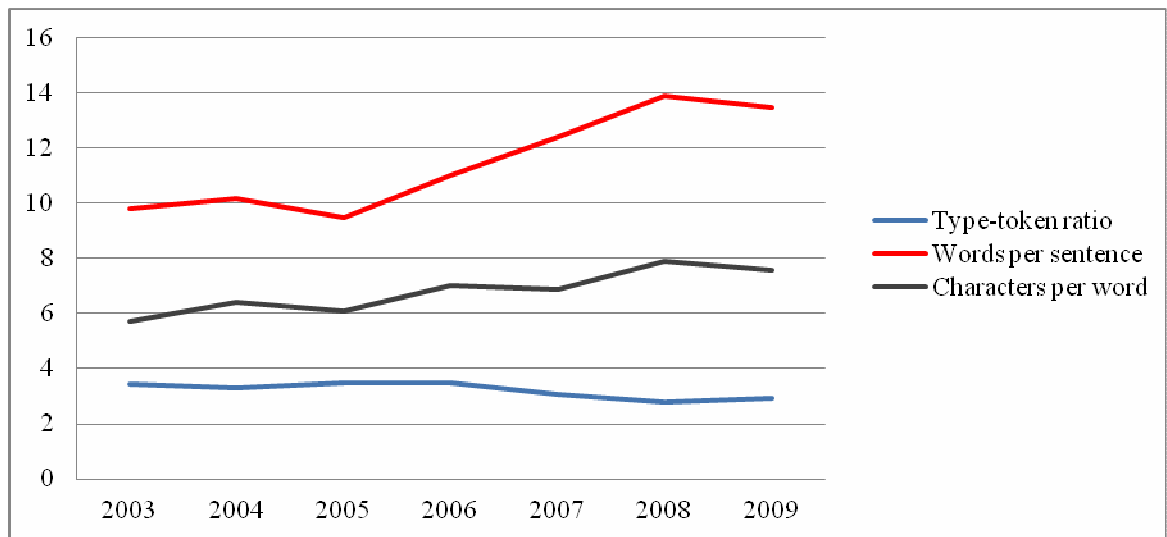


Figure 13: Some linguistic features of fund manager commentaries across the sample years

Finally, I investigate the frequencies of individual keywords across different categories similar to the methodology in Rutherford (2005). In making these pairwise comparisons, I use the Mann-Whitney U test, a powerful, noncategorical, nonparametric test of between-subject differences, to find the differences between frequencies that are significant at the 5% level. Table 8 shows the frequencies of individual words on the consolidated 50 highest-frequency wordlist where there are significant differences in frequency among the seven groups of mutual funds. The word-frequencies reported in Table 8 are averaged across the sample years and normalised based on a 10,000 word document.

Table 8: Word-frequency analysis of different fund categories

Words	Word frequencies per 10,000 words								Statistically significant differences in frequency				
	<i>Loss-Making Funds</i>	<i>Least Profitable Funds</i>	<i>Most Profitable Funds</i>	<i>Smallest Funds</i>	<i>Largest Funds</i>	<i>Value-oriented Funds</i>	<i>Growth-oriented Funds</i>	<i>Average</i>	<i>Loss-making vs. Least Profitable</i>	<i>Least Profitable vs. Most Profitable</i>	<i>Loss-making vs. Most Profitable</i>	<i>Smallest vs. Largest</i>	<i>Value vs. Growth</i>
Financial terms													
Market	105.6	70.4	54.6	64.0	98.8	79.3	82.1	86.2	*	*		*	
Performance	65.2	90.1	102.9	85.5	79.9	66.4	81.3	79.7	*		*		
Growth	60.6	85.8	99.2	84.7	66.2	40.8	105.5	71.1			*	*	*
Index	64.9	35.7	49.9	44.1	49.3	38.8	40.1	44.6	*	*			
Performance terms													
Strong	37.2	43.0	49.1	35.5	39.8	30.3	48.9	40.8			*		
Higher	28.8	37.0	38.0	32.4	32.9	28.1	33.6	32.5	*		*		
Positive	20.0	30.9	35.5	22.0	24.4	20.4	27.6	24.5			*	*	
Profit(s)	34.1	16.7	35.9	21.7	24.4	18.0	21.3	21.4	*	*			
Loss(es)	29.5	13.6	10.0	25.9	10.9	26.8	14.1	18.8	*		*		
Self-reference													
Fund(s)	311.0	251.5	189.5	245.4	235.5	229.9	231.0	234.4	*		*		
We	76.6	135.1	199.0	145.2	151.7	156.7	125.4	133.7			*		
Other terms													
Opportunities	39.1	29.0	28.5	25.5	27.2	20.3	32.8	29.2			*	*	
Long term	40.4	32.5	21.4	25.9	22.2	21.3	28.3	25.0	*				
Because	30.6	25.2	15.9	14.4	20.3	19.6	26.9	18.3	*		*		
Not	38.6	25.0	19.9	27.1	27.3	22.6	26.9	24.4	*		*		

With regards to *financial terms*, the word “market” is more frequently used among funds with negative absolute returns, and the least profitable funds in the positive return category. The same pattern holds for the word “economy”. Although no firm conclusion can be drawn from this observation, it seems to suggest that fund managers, in aggregate, refer to the market and the economy as external performance detractors in a self-serving way, which is consistent with the anecdotal evidence based on close-reading mutual funds in Chapter 5. The frequency of use for “index” yields a similar conclusion, i.e. fund managers tend to make benchmark comparisons more frequently when performance is in the negative domain, and in doing so they strategically shift the reader’s attention away from the fact that they have lost money by investing in the fund.

In contrast, the word “performance” is used more often by the most profitable funds and less so by least profitable funds and loss-making funds. This can be due to the same self-serving attribution bias that leads fund managers to take ownership of favourable performance results. Not surprisingly, the term “growth” is used more frequently by growth-oriented funds, but also more so by most profitable funds. It is, however, difficult to attach significance to the latter, since “growth” may refer to a rise in assets as well as returns, both in the past fiscal year and the anticipated future.

Continuing on to *performance terms*, we can observe that the triad of “strong”, “higher” and “positive” is used more frequently by the most profitable funds. However, the least profitable funds, and even loss-making funds do not use these terms much less frequently. This may be associated with the tendency of fund managers to report negative news in the false positive format (i.e. “the fund did not benefit from positive performance” instead of “our returns were negative”). In fact, the usage frequency of the word “not” is itself suggestive of the well-documented *Pollyanna effect* which can be defined as “the universal human tendency to use evaluatively positive words more frequently and diversely than evaluatively negative words in communicating” (Boucher and Osgood, 1968). With regards to the usage of “profit(s)” and “loss(es)”, our results are similar to Rutherford (2005). Loss-making funds refer to profits more frequently than to losses, and they even make more references to profits than least profitable funds, which provides further support for

the Pollyanna hypothesis. I will test the Pollyanna hypothesis more robustly later in this section.

The use of *self-reference* terms in the commentaries is consistent with the pattern observed in the longitudinal study in Table 8. In other words, loss-making funds tend to use the term “fund” much more frequently than “we” while they begin to refer to themselves using a personal pronoun when performance improves. This is, of course, a clear manifestation of the self-serving attribution bias inherent, more or less, in all economic agents, and by extension, in professional investors.

Finally, some *other terms* in Table 8 merit attention. Loss-making fund managers, compared to their counterparts who have returned a profit, tend to talk more frequently about lost “opportunities” as well “opportunities” for growth in the future. The same applies to growth-oriented funds versus value-oriented funds. Loss-making funds managers also cite “long term” more frequently in comparison. Both of these observations may suggest the same strategy of focusing the reader’s attention on more positive messages. In addition, the word “because” is used more often in the negative domain, for the likely purpose of advancing causal arguments to justify sub-par performance. This observation is also consistent with the anecdotal evidence provided in Chapter 5.

Several of the observations based on Table 8 suggest the existence of the Pollyanna effect which refers to the general tendency to agree with positive statements about oneself. I aim to test this hypothesis more robustly in my large sample using a list of positive and negative words provided in Henry (2008). The list is extensively used in recent studies such as Loughran and McDonald (2010) and Craig, Amernic and Tourish (2010). The list is illustrated in figure 14.

POSITIVITY word list

positive positives success successes successful succeed succeeds succeeding succeeded accomplish accomplishes accomplishing accomplished accomplishment accomplishments strong strength strengths certain certainty definite solid excellent good leading achieve achieves achieved achieving achievement achievements progress progressing deliver delivers delivered delivering leader leading pleased reward rewards rewarding rewarded opportunity opportunities enjoy enjoys enjoying enjoyed encouraged encouraging up increase increases increasing increased rise rises rising rose risen improve improves improving improved improvement improvements strengthen strengthens strengthening strengthened stronger strongest better best more most above record high higher highest greater greatest larger largest grow grows growing grew grown growth expand expands expanding expanded expansion exceed exceeds exceeded exceeding beat beats beating

NEGATIVITY word list

negative negatives fail fails failing failure weak weakness weaknesses difficult difficulty hurdle hurdles obstacle obstacles slump slumps slumping slumped uncertain uncertainty unsettled unfavorable downturn depressed disappoint disappoints disappointing disappointed disappointment risk risks risky threat threats penalty penalties down decrease decreases decreasing decreased decline declines declining declined fall falls falling fell fallen drop drops dropping dropped deteriorate deteriorates deteriorating deteriorated worsen worsens worsening weaken weakens weakening weakened worse worst low lower lowest less least smaller smallest shrink shrinks shrinking shrunk below under challenge challenges challenging challenged

Figure 14: List of positive and negative words, from Henry (2008)

I search for instances of the above positive and negative words in the study corpus using the same categories of funds in terms of performance, i.e. loss-making, least profitable and most profitable. In addition, similar to Rutherford (2005), I explore two relevant categories. The first category is “up” words which generally connote growth or elevation and include “higher” “increase”, “increased”, “more”, “over” and “up”. The second category is “down” words which include “decrease”, “decreased”, “lower”, “reduced” and “reduction”. The word frequencies are averaged across all the sample years and normalised for a document length of 10,000 words. The results are illustrated in Table 9.

Table 9: Word-frequency analysis of positive and negative tone

Words	<i>Loss-Making Funds</i>	<i>Least Profitable Funds</i>	<i>Most Profitable Funds</i>	<i>Average</i>	<i>Loss-making vs. Least Profitable</i>	<i>Least Profitable vs. Most Profitable</i>	<i>Loss-making vs. Most Profitable</i>
Positive words	625.6	618.1	735.2	626.5		*	*
Negative words	251.0	260.5	187.8	255.4			*
“up” words	118.5	115.3	129.7	120.2		*	
“down” words	52.8	51.0	37.5	45.7			*

The results reported in Table 9 suggest that positive words are more often used in fund manager commentaries than negative words (almost 2.4 times as much, which is slightly less than the 3 times proportion Rutherford (2005) found for corporate annual reports), which is another clear manifestation of the Pollyanna effect. What is more, this effect is stronger among loss-making funds compared to least profitable funds, i.e. the fund managers in the former group tend to use more positive words in order to “sugarcoat” the undesirable message they have to communicate to their clients in the commentaries. The results for “up” words and “down” words are similar.

In this section, I demonstrated that key differences exist in the *tone* and *genre* of fund manager commentaries whose corresponding funds have experienced varying degrees of past investment performance. In the following section, I look at a closely related concept: readability. The objective is to understand how the readability of mutual fund reports may be correlated with investment returns.

6.4 THE READABILITY OF FUND MANAGER COMMENTARIES IN LIGHT OF PRIOR PERFORMANCE

This section explores the issue of readability of mutual fund annual reports and its links with current and expected future investment performance. Readability is measured using the well-known *Flesch* index as well as the more appropriate *Plain English* index popularized by Loughran and McDonald (2010). First, I begin by explaining the general concept of readability in accounting and finance literature.

6.4.1 THE CONCEPT OF READABILITY IN FINANCIAL COMMUNICATION

Readability is an important topic in financial communication. If the intended audience of financial disclosures face difficulty in understand their content, the whole process of financial communication may be rendered ineffective. Warren Buffet, one of the greatest investors of our times, describes his own occasional challenge in comprehending financial disclosures:

“There are several possible explanations as to why I and others sometimes stumble over an accounting note or indenture description. Maybe we simply don’t have the technical knowledge to grasp what the writer wishes to convey. Or perhaps the writer doesn’t understand what he or she is talking about. In some cases, moreover, I suspect that a less-than-scrupulous issuer doesn’t want us to understand a subject it feels legally obligated to touch upon.”

(The SEC Plain English Handbook, 1998)

The concept of readability is defined in a number of different ways. While readability generally denotes the ease and speed at which a text can be read and understood, some definitions stress the context-dependency of this construct. In other words, the degree to which certain groups of individuals can comprehend a given text illustrates the readability level for that particular audience. (see Jones and Shoemaker (1994), Hargis, Hernandez, Hughes, Ramaker, Rouiller and Wilde (1998), and Clatworthy and Jones (2001) among others).

In the context of annual reports, prior research has investigated the links between annual report readability and both current as well as future performance. In terms of the impact of current performance on readability, the management obfuscation hypothesis suggests that managers may have incentives to obfuscate information

about poor performance, and they often do so through preparing complicated, less transparent disclosures, as Bloomfield (2002) explains. In fact, according to the obfuscation hypothesis, managers seek to increase the processing cost of adverse information, hoping that such information is not reflected in stock prices or at least incorporated with a delay. There are a large number of empirical studies in support of this strategic behaviour. Jones and Shoemaker (1994) and Li (2008) provide examples of these studies.

With regards to the relation between disclosure readability and the firm's expected future performance, Li (2008) explains how opportunistic managers may be willing to make the annual report less readable if they believe that current good earnings are transitory or poor earnings are persistent. On the other hand, there is incentive for those managers expecting better future performance to disclose information more transparently so that their information-processing costs are lowered and they are distinguished from the "lemons". In other words, "to the extent that complicated annual reports can hide the transitory nature of good news or the permanent nature of bad news by increasing investors' information-processing costs, the management obfuscation hypothesis predicts that the profits (losses) of firms with more complex annual reports are less (more) persistent."

6.4.2 READABILITY OF FUND MANAGER COMMENTARIES AND PERFORMANCE

One can argue that readability is best explored by an operational definition, i.e. by assessing the method or the formula used to measure it. While there are a large number of methods that claim to measure readability, two of them have been often referenced in finance and accounting literature: Gunning (1952)'s *Fog* Index and Flesch (1949)'s eponymous *Flesch* Reading Ease Score. Both measures, which are derived from the computational linguistics literature, use the number of words per sentence and the number of syllables per word to create a combined measure of readability. The *Flesch* score is arguably more precise than the *Fog* score since the latter treats, in a binary way, all words consisting of three and more syllables as

potentially decreasing readability. The *Flesch* score, however, takes the exact number of word syllables into account. The formula for computing the *Flesch* score is:

$$\text{Flesch Reading Ease Score} = 206.835 - 0.846 * WL - 1.015 * SL$$

where:

WL = number of syllables per 100 words

SL = average number of words per sentence

The *Flesch* formula is arranged such that a higher score denotes more readability (See figure 15).

Reading ease rating	Difficulty	Educational level	Typical magazine style
0-30	Very difficult	Postgraduate	Scientific
30-50	Difficult	Undergraduate	Academic
50-60	Fairly difficult	Grade 10-12	Quality
60-70	Standard	Grade 8-9	Digest
70-80	Fairly easy	Grade 7	Slick fiction
80-90	Easy	Grade 6	Pulp fiction
90-100	Very easy	Grade 5	Comic

Figure 15: The *Flesch* reading ease score and typical readability

While *Fog* and *Flesch* are widely used readability measures in accounting and finance literature, Loughran and McDonald (2010) argue that, in general, syllable counts cannot produce robust measures of corporate disclosure readability. They demonstrate that the top-quartile of multi-syllable words in these reports (including such commonly used words as *corporation*, *company*, *directors*, *executive*, etc.) is often easy to understand for an “average” investor. The authors propose that the *Plain English* standardized guidelines proposed by the SEC can provide a more robust measure of annual report readability using which should reduce measurement errors and attenuation bias in regression tests. They further show that among the above three readability measures, only *Plain English* is significantly linked to equity issuance, and only *Plain English* and *Flesch* are correlated with a share-holder friendly corporate governance structure.

The *Plain English* guidelines came into force in 1998 with the following specification which is mandatory for prospectuses and highly recommended for other disclosures:

“Companies filing registration statements under the Securities Act of 1933 must: (1) write the forepart of these registration statements in plain English; (2) write the remaining portions of these registration statements in a clear, understandable manner; and (3) design these registration statements to be visually inviting and easy to read.” (SEC Staff Legal Bulletin No.7)

The Rule 421(d) specification further illustrates the *Plain English* requirements:

“Substantially comply with these plain English principles: (1) short sentences; (2) definite, concrete everyday language; (3) active voice; (4) tabular presentation of complex information; (5) no legal jargon; and (6) no multiple negatives.”

In this section, I use the *Flesch* score, as defined above, as well as the *Plain English* measure developed by Loughran and McDonald (2010) to investigate the readability of mutual fund annual reports. Loughran and McDonald (2010)'s *Plain English* measure incorporates six components including sentence length, word length, personal pronouns, and other style directives. They design a proprietary computer program to compute this measure based on each given text in the following way:

- (1) Sentence length: The average number of words per sentence in the document is calculated according to the Rule 421(d) and the specific examples in the Plain English Handbook (e.g., pp. 28-29).
- (2) Average word length: Following SEC's recommendation for using “short, common words”, this component is calculated by counting the character length of each word and averaging across all words in the document.
- (3) Passive: It is important to avoid passive voice to improve readability, as the SEC Handbook (pp. 19-21) highlights. To calculate this readability component, I use Loughran and McDonald's approach to look for different auxiliary verb variants of “to be” including: “to be”, “to have”,

“will be”, “has been”, “have been”, “had been”, “will have been”, “being”, “am”, “are”, “is”, “was”, and “were”, as well as auxiliary verbs followed by a the “ed” ending or one of the commonly known 158 irregular verbs.

- (4) Legalese: The SEC Staff Legal Bulletin³² identifies certain words and phrases as inappropriate legal jargon (e.g., “set forth under” or “hereinafter”). Loughran and McDonald look for a list of 12 phrases and 48 words of this nature.
- (5) Personal pronouns: The SEC Handbook (p. 22) recommends using personal pronouns as they can “dramatically” improve the readability of the report. The first-person plural and second-person personal pronouns (i.e. “we”, “us”, “our”, “ours”, “you”, “your”, “yours”) are searched.
- (6) Other: Loughran and McDonald (2010) also combine a number of less frequently used categories identified in the Handbook including negative phrases, superfluous words and the use of the word “respectively” (pp. 17-35). They search for (1) a list of 11 negative compound phrases (e.g., “not unlike” or “not... unless”); (2) a list of eight superfluous phrases (e.g., “despite the fact that” or “in the event that”); and (3) occurrences of the word “respectively”.

I use the *Concordance* program to circumvent the problem of not having access to the proprietary computer program used by Loughran and McDonald (2010). In doing so, I simplify the analysis by combing all the fund manager commentaries in a given category in one text file. Since both *Flesch* and *Plain English* measures are computed using linear formulae, and since the fund manager commentaries are each roughly around 700 words long, this simplification does not introduce any major measurement bias.

³² The Bulletin can be accessed at <http://www.sec.gov/interp/legals/cfslb7a.htm>. A list of such legalese and industry jargons is provided in Appendix 6.

Concordance easily provides such global statistics as the number of lines, words (“tokens”), distinct words (“types”), characters, sentences, words per sentence, type-token ratio, etc. Hence, I use the above statistics as well as the program’s selective concordancing capability to build the *Plain English* measure in a similar way to Loughran and McDonald (2010).

I specifically aim to test the following hypothesis in this section: “There is no significant difference in the *readability* of fund manager commentaries whose corresponding funds have experienced varying degrees of past investment performance, *ceteris paribus*.” Therefore, I use the same fund performance categories as used in Rutherford (2005) to trace the readability of various mutual fund commentaries. While *Plain English* and *Flesch* are used to measure readability, the *type-token ratio* (ratio of distinct words to total words) and *narrative length* (number of total words) are used as measures of verbosity. The results are reported in Table 10.

Table 10: Readability analysis of various fund categories in the study corpus

		<i>Loss-Making Funds</i>	<i>Least Profitable Funds</i>	<i>Most Profitable Funds</i>	<i>Average</i>	<i>Loss-making vs. Least Profitable</i>	<i>Least Profitable vs. Most Profitable</i>	<i>Loss-making vs. Most Profitable</i>
<u>Verbosity</u>	Type-token Ratio	2.7	3.3	3.2	3.0			
	Length	750	646	655	682	*		
<u>Readability</u>	<i>Flesch Score</i>	22.4	31.1	39.6	30.2			*
	<i>Plain English</i>	-0.98	-0.56	0.13	-0.65		*	*

The results suggest that loss-making funds are less readable and slightly more verbose than least profitable funds, which are in turn less readable and ever so more verbose than the most profitable funds. While *Plain English* clearly shows a significant difference between the readability levels of the three fund groups, the *Flesch* score also shows a similar pattern in aggregate, which, at least in the case of mutual fund reports, does not seem to support Loughran and McDonald's claim about the inferiority of *Flesch* as a readability measure.

The verbosity of the commentaries is closely related with the readability, i.e. the loss-making funds appear to be slightly more verbose on average, although the difference between the fund groups is, except in one case, not significant at the 5% level using the Mann-Whitney U test. This may be due to the fact that investment companies have to file annual reports with the SEC that adhere to the industry conventions in terms of structure and length, and due to the large number of mandatory performance tables and schedules that need to be included in the annual reports, fund managers cannot influence the length of the commentary to a large extent.

6.5 HOW DOES OVERCONFIDENCE RELATE TO PAST PERFORMANCE?

Gervais and Odean (2001), extending their earlier work in Odean (1999), develop a model to explain the process in which financial agents become overconfident by learning about their own ability and past performance. They argue that initially, financial agents do not recognize their ability, but in the course of time and with accumulating more experience, they attribute successful outcomes to their superior judgements, and failure to external factors or chance. Hence, they “learn” to become overconfident through time. This mechanism, which has a net positive impact on overconfidence, can be coupled with the weakening or distortion of information signals triggered by anxiety, as outlined in the conceptual model introduced earlier in the thesis and reiterated below. In other words, it is reasonable to expect a similar pattern among mutual fund managers such that their overconfidence level should vary subject to prior investment performance.

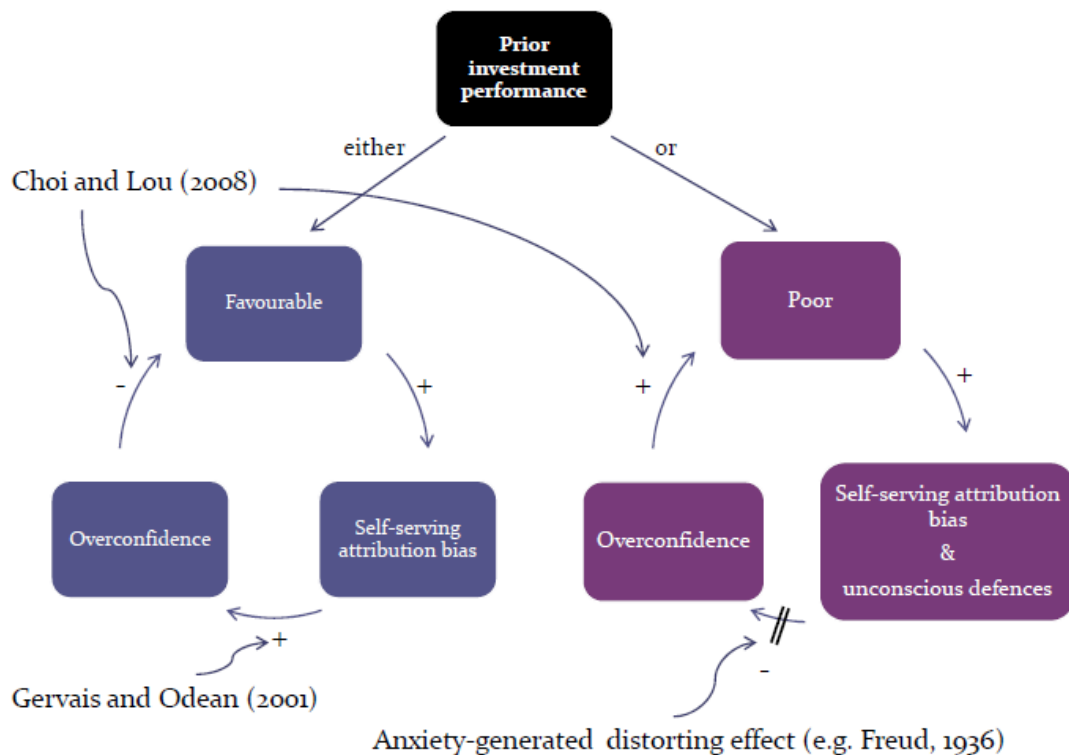


Figure 16: The dynamic interaction between self-serving attribution bias and overconfidence

In order to measure the degree of this co-variation, I rank the funds in each year on prior-year Carhart alphas and form decile portfolios. Then, I combine all the extreme (top and bottom) deciles across 2003-2009 and use the t-test with unequal variance to measure the difference between the two groups. The results are displayed in Table 11 Panel A. I reiterate this analysis based on funds ranked by prior three-year alphas (Panel B).

Table 11: Variation of fund manager overconfidence in extreme portfolios sorted on prior Carhart alphas

This table compares the top and bottom deciles formed by sorting the funds in each year on prior-year Carhart alphas and combining all the extreme deciles across 2003-2009. *, **, *** indicate significance at 10%, 5% and 1% levels based on two-tailed tests.

Panel A:

	Top Decile of Carhart Alpha (PRIYR)		Bottom Decile of Carhart Alpha (PRIYR)		t-test with unequal var
	Mean	SD	Mean	SD	
Optimism	55.931	2.097	49.737	1.955	2.544**
Certainty	51.013	2.255	45.634	2.210	2.339**
Self-reference	1.944	0.249	1.095	0.251	1.895*

Panel B:

	Top Decile of Carhart Alpha (PR3YR)		Bottom Decile of Carhart Alpha (PR3YR)		t-test with unequal var
	Mean	SD	Mean	SD	
Optimism	54.140	2.115	50.206	2.183	2.218**
Certainty	51.637	2.047	45.792	2.306	1.982**
Self-reference	2.043	0.285	1.266	0.262	1.635

It can be inferred that prior positive performance, both during the previous one-year and previous three-year periods, generates excess optimism as well as certainty as

expected and the difference between the extreme deciles for both variables is significant at the 5% level. In fact, funds belonging to the top decile of Carhart alpha have a mean optimism which is, on average, about three standard deviations higher than the funds belonging to the bottom decile in the case of previous one-year alpha. The difference between the two deciles when funds are ranked by previous three-year alphas is similar but less pronounced. The effect of prior performance on fund manager certainty is also similar.

The difference between the funds in the two extreme deciles in terms of self-reference is also significant in the case of previous one-year alpha, although at the 10% significance level. This is in line with the anecdotal examples of manual content analysis in Chapter 5 which suggest that high-performing fund managers tend to refer to themselves more often than their poor-performing counterparts.

Alternatively, I investigate this effect using a parallel method starting from fund-manager expressed attributes. First, the funds are sorted in each year on fund manager-expressed optimism, certainty, and self-reference scores. Then, decile portfolios are similarly formed and all the extreme deciles across 2003-2009 are combined. The average prior-year Carhart alphas of top and bottom deciles are then compared using the same t-test. Results are in Table 12.

Table 12: Variation of Carhart alphas in extreme portfolios sorted on fund manager overconfidence

This table compares the average prior-year Carhart alphas of top and bottom deciles formed by sorting the funds in each year on fund manager-expressed optimism, certainty, and self-reference, and then combining all the extreme deciles across 2003-2009.

Variables	<u>Top Decile</u>		<u>Bottom Decile</u>		T-test with unequal variance
	Mean	S.D.	Mean	S.D.	
Average alpha of Optimism -sorted decile portfolio	0.0097	0.0055	0.0041	0.0049	1.877*
Average alpha of Certainty -sorted decile portfolio	0.0076	0.0049	0.0030	0.0027	1.660*
Average alpha of Self-reference sorted portfolio	0.0072	0.0053	0.0036	0.0044	1.912*

In a similar way, these results indicate that, on average, fund managers who adopt a more optimistic, certain and self-referring approach in writing their reports to shareholders have higher previous-year alphas compared to the other group. Therefore, it is important to account for the role of prior performance before interpreting any cross-sectional variation in fund returns that may be marginally explained by certain differences in fund manager characteristics. However, as I note above, the Carhart model already captures the previous-year momentum effect which has a relatively low correlation with the overconfidence scores used in this study.

It is also interesting to investigate the effect of prior performance on a fixed cohort of fund managers through time. The conceptual model explained above leads us to the expectation that in an alternating round of prior performance outcomes, the average fund manager's level of inherent overconfidence is likely to increase, *ceteris paribus*. I attempt to test this hypothesis by tracing the overconfidence proxies of all eligible fund managers in 2003 and following the same cohort during the subsequent six

years until 2009. Results reported in Table 13 demonstrate that mean optimism and mean self-reference both tend to rise with fund manager duration.

Table 13: Does fund-manager expressed overconfidence increase by fund manager duration?

This table reports the mean optimism/certainty/self-reference scores for a given cohort of fund managers starting in 2003 and finishing in 2009 or earlier if the fund manager leaves the fund or the fund terminates.

Year	n.	Optimism	Certainty	Self-reference
2003	2870	51.318	47.129	1.167
2004	2679	52.213	47.118	1.197
2005	2551	52.916	47.292	1.281
2006	2317	53.610	48.324	1.256
2007	2019	54.227	46.395	1.319
2008	1720	54.971	47.286	1.367
2009	1296	55.103	47.259	1.390

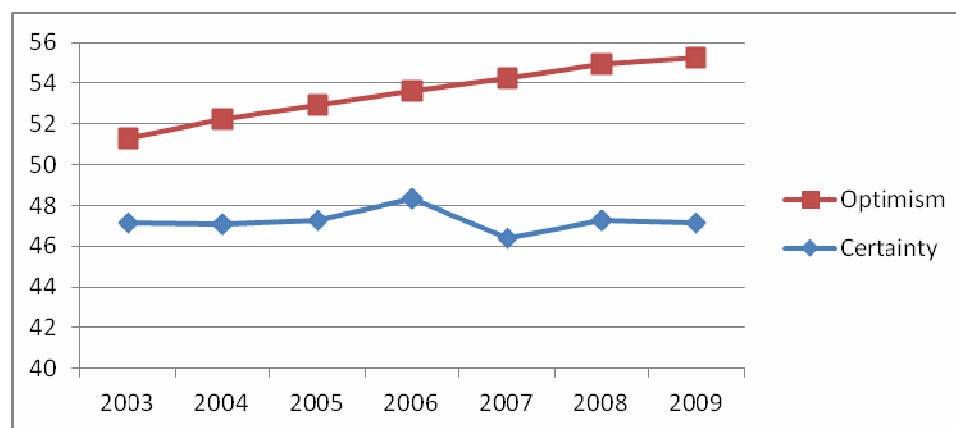


Figure 17: Variation of optimism and certainty by fund manager duration

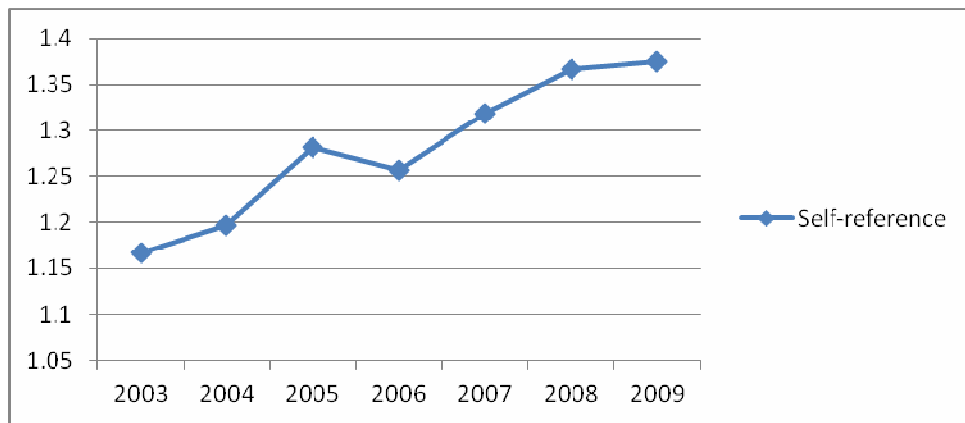


Figure 18: Variation of self-reference by fund manager duration

This dynamic change in overconfidence proxies is better illustrated in figure 17 and figure 18 which indicate that both optimism and self-reference tend to rise during the sample years, further confirming the findings in Chapter 6 using the corpus-linguistic approach.³³

6.6 SUMMARY AND CONCLUSIONS

Several points can be taken away from the findings in this chapter. First, from the perspective of genre analysis and corpus linguistics, fund managers write their reports in distinguishably different genres depending, among others, on their past performance record, their size and their investment style. The hypothesis regarding the existence of distinct rhetorical genres (different fund manager tone) subject to prior performance is supported using a number of cross-sectional tests.

In addition, I establish in a longitudinal study that the overall economic environment in which fund managers operate does influence the tone of fund manager reports in

³³ While this observation is not robust to survivorship bias, one may hypothesize that the growing overconfidence accumulated in this way, on average, leads fund managers to make sub-optimal investment decisions causing adverse performance, as Choi and Lou (2008) demonstrate using the Active Share method. In addition, there is significant literature on the topic of “escalating commitments” in psychology which can provide traction here. I am grateful to Prof. Nick Oliver for making this last comment.

aggregate. The results also provide support for the *Pollyanna* hypothesis, particularly among a number of categories such as loss-making funds. These findings, together with the evidence on readability, are consistent with the close-reading evidence from the previous chapter. To a certain extent, one may be able to conclude that fund managers *strategically* adjust the overall tone and rhetoric of their reports in a self-serving way. However, it is equally plausible for this behaviour to stem from the unconscious psychological processes that are in play in the mind of the fund manager, since, as it is often demonstrated in this study, the underlying investment story can be an excellent sense-making implement for the professional investor in general.

In the final section of the chapter, I demonstrated cross-sectional variations suggesting that superior past performance boosts overconfidence as measured by all proxies used which is in line with theoretical expectations. The following chapter continues the study by empirically investigating the impact of fund manager overconfidence on future investment returns. I use the well known Carhart asset pricing model as the basis of an empirical model which I seek to improve by adding independent variables proxying for fund manager psychological attributes.

7.1 INTRODUCTION

This chapter seeks to investigate the dynamic relationship between fund-manager expressed overconfidence and the investment performance of a mutual fund. The areas of focus in this chapter 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. I use the well known Carhart asset pricing model as the basis of an empirical model which I seek to improve by adding independent variables proxying for fund manager psychological attributes. The chapter includes controls for other potential confounding factors, and tests the overall robustness of the empirical model. I 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*.

The chapter is organised as follows: Section 7.2 addresses the question of who writes the fund manager commentaries and its relevance to the research results. This section also outlines the structure of the annual reports and explains which parts of the report are content-analysed. Section 7.3 discusses the measures of overconfidence used in this chapter and provides relevant descriptive statistics. Section 7.4 uses a number of empirical methods to explore how fund manager overconfidence and associated measures may impact future investment performance. Finally, section 7.5 summarises and concludes the chapter.

7.2 AUTHORSHIP AND STRUCTURE OF FUND MANAGER COMMENTARIES

It is of course important to discuss the authorship of the mutual fund annual reports for the purposes of this study. Firstly, I argue that according to the conventions in the mutual fund industry, fund managers 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 (the researcher learnt about this convention in conversation with a number of mutual fund managers).³⁴ 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, a similar pattern is observed in CEO communication and the research on CEO letters, speeches, etc. Fund managers, like CEOs, are signatories of their reports and assume legal responsibility for their content. According to Amernic, Craig and Tourish (2010), this attribute 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

³⁴ The conversations took place during 2007 and 2008 with fund managers and public relations staff that I came across in various conferences and, in particular, in a number of meetings in *Martin Currie Investments*, UK.

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.

Since the overconfidence proxies used in this research are based on textual data in the annual reports, it is important to select the appropriate sections of the annual report for relevant study. The body of mutual fund annual reports filed in Edgar typically consists of several sections, including the *president's (chairman's) letter*, *individual fund manager commentaries*, *schedule of portfolio investments*, *financial statements*, *financial highlights*, *notes to financial statements*, *report of independent public accounting firm* and *schedule of shareholder expenses*. Among these sections, only the president's letter and fund commentaries by individual fund managers contain non-quantitative information useful for my study purposes. Often, the president and the fund manager narrate different but complementary sections of the investment story, demonstrating the concept of contrasting narrators. Since the individual fund managers are often solely responsible for making investment decisions, the fund manager commentaries, compared to the president's letter, are likely to provide more leverage in understanding any relation between the manager's state of mind and past or future performance. Although the president's letter can provide investors with a useful big picture of the investment company's present circumstances, it is often too broad to be helpful for the purposes of this study. In contrast, the fund manager commentary is an information-rich section of the annual report which helps explain the past performance of the fund and portray its likely short-term and long-term future performance.

These narratives are less homogeneous compared to corporate annual reports (10-K reports). However, they often include sections on *investment strategy*, *market environment*, *discussion of past performance*, *sector by sector analysis* and the *fund outlook*. Although these sections of the commentary often form a single narrative, sometimes, particularly in the case of underperformance, fund managers choose the sub-genre of question and answer to communicate to investors.

In my content analysis performed mostly by the *Diction* program, the *optimism* scores calculated 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. The reason for dividing up each annual report in this way is to increase accuracy of measuring overconfidence. The fund outlook section, by definition, is where the fund manager writes about his or her views on the fund's possible performance in the future, and therefore, this section of the narrative often lends itself to an optimistic or pessimistic tone of voice. Similarly, the discussion on past performance is an appropriate place to look for occasions of self-reference since managers are inclined, often in a self-serving way, to take ownership of their performance record when they write about it in this section. For the certainty variable, however, it is best to look at the whole commentary as it can come through in both the discussion of the past performance and the fund manager's projections about the future.

7.3 MEASURES OF OVERCONFIDENCE USED IN THIS CHAPTER

The overconfidence effect, in general terms, can be measured in a number of different ways. Hoffrage (2004) lists some of the most common approaches: (1) subjects can be requested to evaluate their own confidence in a statement, and then all the statements with a given level of confidence can be grouped together and be compared that to the actual frequency of being correct; (2) subjects can be tested with multiple-choice questions and then their level of confidence in their answers can be elicited on a scale from chance to total certainty by comparing this to the true accuracy of their answers; (3) subjects can be asked to choose confidence intervals in

response to questions with numerical answers; and (4) subjects can be given the opportunity to bet on the correctness of their answers with chances that are favourable if their judgements of accuracy are correct, which means that they lose money if they are overconfident.³⁵

In the context of finance and accounting, some of the proxies used for measuring overconfidence include *trading activity*, *managerial option exercise* and *active share*. The pros and cons of each of these proxies are discussed in detail in chapter 2 where I establish that while the above measures can work robustly for corporate managers, they are somewhat handicapped when applied to professional investors. Hence, I employ a more straightforward approach to measuring overconfidence which includes content analysing various sections of fund manager reports.

I specifically look at *optimism*, *certainty* and *self-reference* of fund manager commentaries to infer the overconfidence of their corresponding managers. Full description, definitions and formulas for calculating these measures are provided in chapter 4. Table 14 summarises the descriptive statistics provided there for the research variables used in this study based on sample A.

³⁵ Assuming that the human confidence has perfect calibration, judgments with 100% confidence should be correct 100% of the time, 80% confidence correct 80% of the time, etc. By contrast, research findings suggest that confidence exceeds accuracy so long as individuals are answering hard questions about unfamiliar topics. For example, subjects were correct about 80% of the time when they were “100% certain” about their performance in a spelling task (Adams and Adams, 1960).

Table 14: Descriptive statistics of overconfidence proxies

This table reports the distribution of selected overconfidence proxies based on the content analysis of fund manager narratives. 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	1 st Quart	Med	3 rd 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 19 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 14, 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. However, this observation may equally be explained by survival issues. A similar distribution exists for the certainty and self-reference measures.³⁶

³⁶ I also tried winsorising the data using a 90% window which led to similar results.

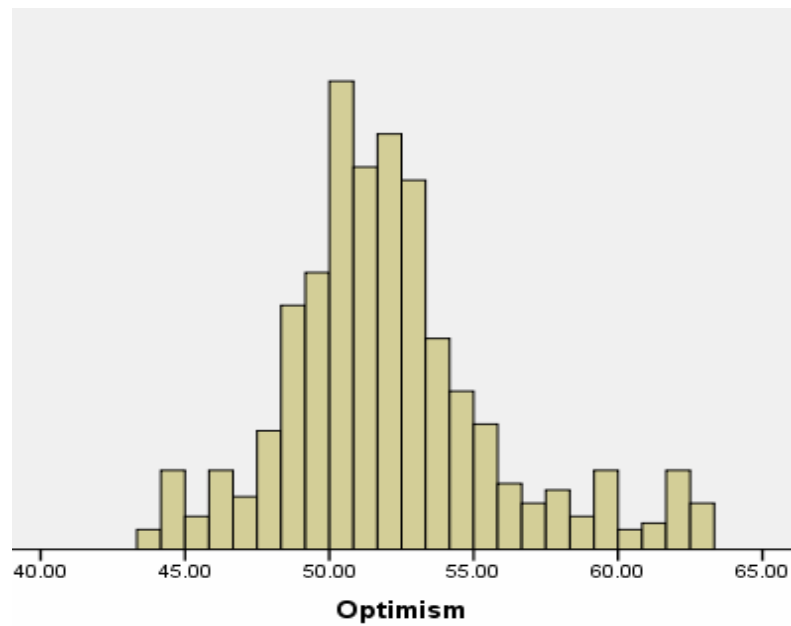


Figure 19: Histogram of the distribution of fund manager optimism scores during an average sample year

Table 15 reports the 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 15: Cross-correlation matrix for main 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 also a significant correlation between optimism and self-reference which is consistent with the expectations and the empirical evidence demonstrated in the previous two chapters.

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 which is distinct from other previously studied factors that influence investment performance.

7.4 HOW DOES OVERCONFIDENCE AFFECT FUTURE INVESTMENT PERFORMANCE OF MUTUAL FUNDS?

7.4.1 OVERVIEW

In this section, I test the hypothesis that excessive levels of overconfidence interfere with sound investment decision-making and thereby diminish future investment returns. In other words, I 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*.”

As explained in detail in Chapter 3, the well-known Carhart model is used as the base regression model to test the research hypotheses in this chapter. The Carhart (1997) model builds on the Fama-French three-factor model by adding prior-year momentum which, for the purpose of this research, adequately captures the effect of previous performance.³⁷ 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.

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

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

7.4.2 THE PORTFOLIO-TRACKING APPROACH

In this section, I 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.

³⁷ In conversations with Prof. Keith Cuthbertson and Prof. Taffler, it was agreed that a simple four-factor regression model such as Carhart should have adequate accuracy in studying the impact of fund manager psychological attributes on performance.

Following this methodology, I rank my 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 the purpose of consistency, I perform the portfolio sorts in the end of March in each year.³⁸ Following this ranking month, each portfolio is held for twelve months and the time-series of monthly portfolio excess returns (i.e. average cross-sectional fund 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, I test a hedge strategy inspired by the research hypotheses in this chapter. 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? I construct a long-short portfolio strategy based on shorting the portfolio with the highest level of overconfidence (P10) and going long in the portfolio with a lower level of overconfidence. I do the long stage in two ways. In the *Hedge1* strategy, I long the portfolio with the lowest level of confidence (P1) and in the *Hedge2* strategy, I 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.

As explained in the literature review in Chapter 2, 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, I expect the *Hedge2* strategy to capture higher positive abnormal returns compared to the *Hedge1*

³⁸ 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.

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, one might expect “reasonably” confident fund managers (i.e. those with an average, “normal” confidence level) to make better investment decisions compared to their peers and thus produce higher returns, *ceteris paribus*.

In order to test the significance of the abnormal returns using the Carhart (1997) four-factor model, I 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 20.

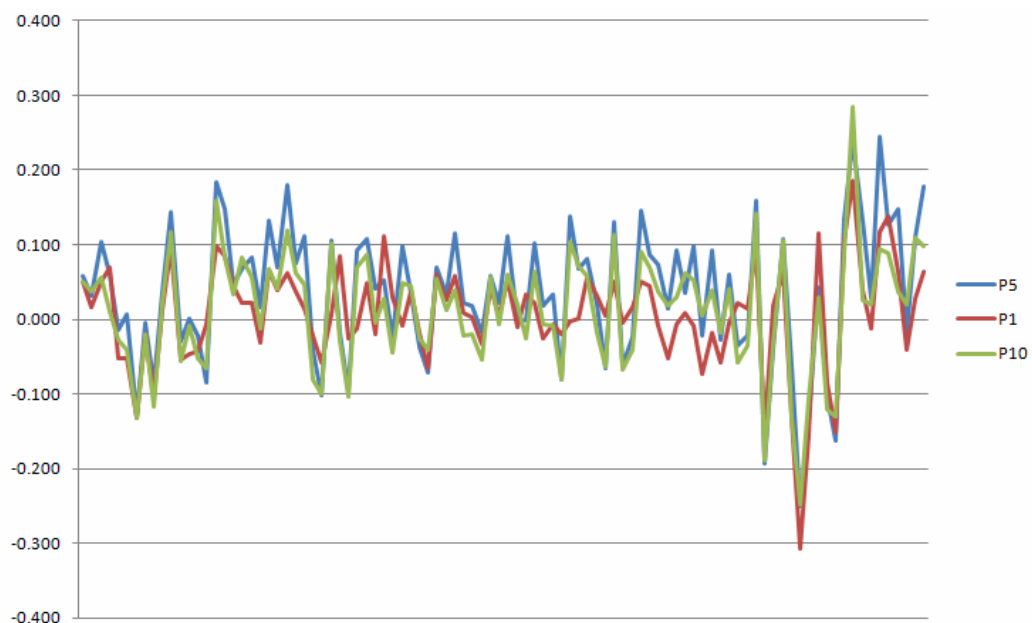


Figure 20: Monthly average excess returns of extreme decile portfolios and an intermediate portfolio based on OPTIMISM scores

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 the above figure 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, I perform the required monthly time-series regressions for each portfolio as in Barber and Odean (2001) and Kumar and Lee (2006). Therefore, I use the following equation in Table 16:

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

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

Table 16: The impact of fund manager overconfidence on excess returns, using portfolio-tracking analysis

Sample funds are sorted into decile portfolios based on prior year OPTMISM 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 OPTMISM scores

	<i>P1</i>	<i>P2</i>	<i>P3</i>	<i>P4</i>	<i>P5</i>	<i>P6</i>	<i>P7</i>	<i>P8</i>	<i>P9</i>	<i>P10</i>	<i>Hedge1</i> <i>returns</i>	<i>Hedge2</i> <i>returns</i>
Rm-Rf	1.067*** (0.000)	1.011*** (0.000)	0.918*** (0.000)	0.933*** (0.000)	1.182*** (0.000)	1.072*** (0.000)	1.005*** (0.000)	0.916*** (0.000)	0.949*** (0.000)	1.052*** (0.000)	0.015*** (0.000)	0.130*** (0.001)
SMB	0.494*** (0.000)	0.450*** (0.001)	0.397*** (0.001)	0.426*** (0.002)	0.406*** (0.000)	0.401*** (0.000)	0.389*** (0.000)	0.356*** (0.003)	0.337*** (0.000)	0.314*** (0.000)	0.180** (0.032)	0.092*** (0.008)
HML	0.644*** (0.000)	0.686*** (0.000)	0.656*** (0.000)	0.589*** (0.001)	0.577*** (0.000)	0.586*** (0.000)	0.578*** (0.000)	0.598*** (0.000)	0.628*** (0.000)	0.551*** (0.000)	0.093*** (0.002)	0.026** (0.018)
MOM	-0.209*** (0.000)	-0.276*** (0.003)	-0.350*** (0.001)	-0.201*** (0.000)	-0.185*** (0.005)	-0.224*** (0.000)	-0.271*** (0.000)	-0.153*** (0.004)	-0.108*** (0.000)	-0.176*** (0.002)	-0.033** (0.026)	-0.009** (0.030)
Alpha	0.00063 (0.216)	-0.00027 (0.365)	0.00140 (0.219)	0.00183* (0.071)	0.00177* (0.090)	0.00096 (0.197)	0.00108 (0.376)	0.00055 (0.641)	-0.0004 (0.365)	-0.00067* (0.093)	0.00130 (0.292)	0.00244* (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 16: Continued

Sample funds are sorted into decile portfolios based on prior year CERTAINTY 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 B: Fund portfolios formed on CERTAINTY scores

	<i>P1</i>	<i>P2</i>	<i>P3</i>	<i>P4</i>	<i>P5</i>	<i>P6</i>	<i>P7</i>	<i>P8</i>	<i>P9</i>	<i>P10</i>	<i>Hedge1</i> <i>returns</i>	<i>Hedge2</i> <i>returns</i>
Rm-Rf	1.132*** (0.000)	0.911*** (0.000)	0.995*** (0.000)	1.208*** (0.000)	1.085*** (0.000)	0.877*** (0.000)	1.101*** (0.000)	1.106*** (0.000)	0.902*** (0.000)	0.930*** (0.000)	0.172*** (0.001)	0.115*** (0.002)
SMB	0.524*** (0.000)	0.409*** (0.001)	0.448*** (0.001)	0.516*** (0.002)	0.577*** (0.000)	0.529*** (0.000)	0.479*** (0.000)	0.401*** (0.003)	0.359*** (0.000)	0.388*** (0.000)	0.136*** (0.009)	0.189*** (0.004)
HML	0.627*** (0.000)	0.582*** (0.000)	0.690*** (0.000)	0.619*** (0.001)	0.556*** (0.000)	0.550*** (0.000)	0.521*** (0.000)	0.583*** (0.000)	0.503*** (0.000)	0.484*** (0.000)	0.143*** (0.006)	0.072*** (0.006)
MOM	-0.178*** (0.000)	-0.219*** (0.002)	-0.235*** (0.007)	-0.274*** (0.000)	-0.270*** (0.005)	-0.282*** (0.000)	-0.233*** (0.003)	-0.209*** (0.003)	-0.190*** (0.000)	-0.191*** (0.001)	-0.079* (0.088)	0.013** (0.045)
Alpha	0.00094 (0.310)	0.00025 (0.456)	-0.00040 (0.370)	0.00068 (0.241)	0.00105* (0.091)	0.00209* (0.088)	0.00101 (0.166)	0.00050 (0.351)	-0.00094 (0.580)	-0.00133 (0.843)	0.00227 (0.717)	0.00238 (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 16: Continued

Sample funds are sorted into decile portfolios based on prior year SELF-REFERENCE 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 C: Fund portfolios formed on SELF-REFERENCE scores

	<i>P1</i>	<i>P2</i>	<i>P3</i>	<i>P4</i>	<i>P5</i>	<i>P6</i>	<i>P7</i>	<i>P8</i>	<i>P9</i>	<i>P10</i>	<i>Hedge1</i> <i>returns</i>	<i>Hedge2</i> <i>returns</i>
Rm-Rf	0.883*** (0.000)	0.917*** (0.000)	0.955*** (0.000)	0.990*** (0.000)	1.034*** (0.000)	1.007*** (0.000)	1.045*** (0.000)	1.015*** (0.000)	0.922*** (0.000)	0.874*** (0.000)	0.009*** (0.000)	0.160*** (0.000)
SMB	0.338*** (0.000)	0.391*** (0.004)	0.407*** (0.000)	0.433*** (0.000)	0.412*** (0.001)	0.365*** (0.000)	0.369*** (0.000)	0.320*** (0.002)	0.375*** (0.000)	0.399*** (0.000)	-0.061*** (0.002)	0.013*** (0.001)
HML	0.715*** (0.000)	0.692** (0.002)	0.636*** (0.000)	0.680*** (0.001)	0.729*** (0.000)	0.762*** (0.000)	0.771*** (0.000)	0.677*** (0.001)	0.663*** (0.000)	0.601*** (0.000)	0.114** (0.011)	0.128*** (0.005)
MOM	-0.205*** (0.000)	-0.179*** (0.000)	-0.199*** (0.001)	-0.217*** (0.000)	-0.217*** (0.000)	-0.238*** (0.000)	-0.190*** (0.000)	-0.163*** (0.000)	-0.161*** (0.000)	-0.147*** (0.000)	-0.058*** (0.008)	-0.070** (0.035)
Alpha	-0.00018 (0.312)	0.00023 (0.455)	0.00085 (0.479)	0.00105 (0.570)	0.00139 (0.432)	0.00092 (0.308)	0.00092 (0.515)	0.00041 (0.722)	-0.00006 (0.532)	-0.00029 (0.538)	0.001 (0.292)	0.00168 (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 16 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. I 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-REFERENCE 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.

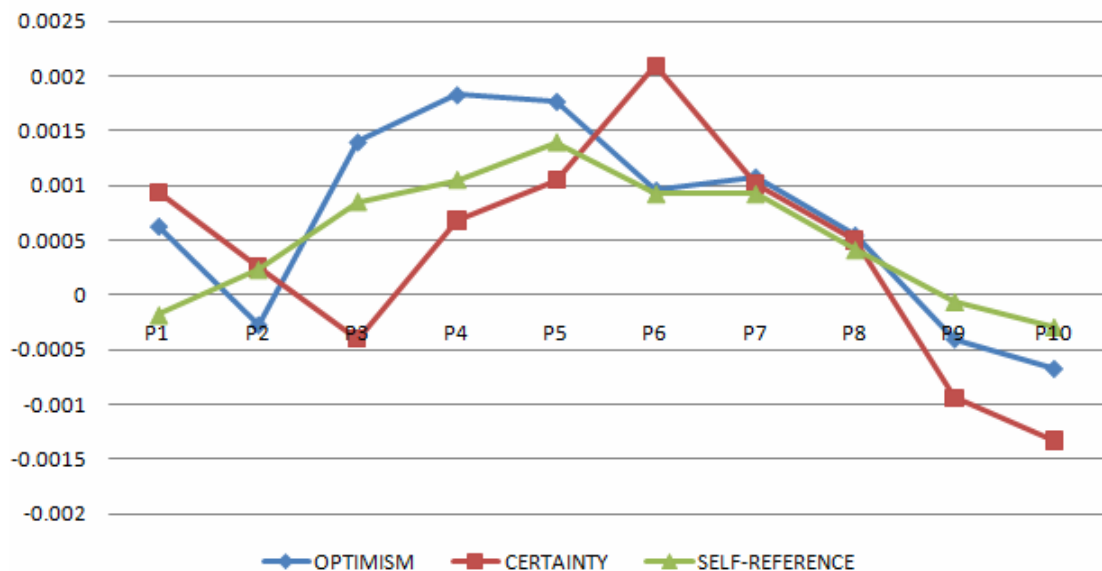


Figure 21: Average abnormal excess returns of ten equally weighted decile portfolios ranked by previous-year overconfidence proxies

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 longing funds with normally (over)confident managers. The corresponding return in the case of SELF-REFERENCE is 2%. On the other hand, the *Hedge1* strategy, based on shorting funds with extremely overconfident fund managers and longing funds with the least (over)confident fund managers, captures 1.6% based on OPTIMISM 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 21 above.

7.4.3 THE CALENDAR TIME APPROACH

In this section, I employ the *calendar time portfolio approach* which is one of the most widely used techniques for analysing risk-adjusted investment performance.³⁹ 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

³⁹ The calendar time portfolio approach has many different applications in empirical finance, such as, for example, studying the performance of private investors (e.g., Barber and Odean, 2000, 2001; Kumar and Lee, 2006), the long-run performance of stocks (e.g., Fama, 1998; Mitchell and Stafford, 2000), insider trading (e.g., Jeng, Metrick, and Zeckhauser, 2003), and in the performance analysis of investment funds (e.g., Fama and French, 2003; Fung, Hsieh, Naik, and Ramadorai, 2008) which is of interest in this study.

dependence amongst individual fund returns is eliminated (Hoechle, Schmid and Zimmerman, 2009).

For each fund-year observation during 2003-09, I calculate Carhart alpha using 36 monthly returns from month -24 to month 12 (month 0 being the publication month of the annual report).⁴⁰ Pooled cross-sectional time-series regressions are used to capture the effect of overconfidence on future investment returns using the following general equation:

$$E(R_{it}) - R_{ft} = \beta_0 + \beta_{1i}[E(R_{mt}) - R_{ft}] + \beta_{2i}E(\text{SMB}_t) + \beta_{3i}E(\text{HML}_t) + \beta_{4i}E(\text{MOM}_t) \\ + \beta_{5i}\text{OPTIMISM}_{it} + \beta_{6i}\text{CERTAINTY}_{it} + \beta_{7i}\text{SELF-REFERENCE}_{it}$$

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

I 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. I 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 $\text{OPTIMISM}_{i200604}$ up to $\text{OPTIMISM}_{i200703}$ will be set to 1. Finally, I initially exclude year fixed effects from the model, and then add them to the model in order to compare the results.

Table 17 shows the results of the panel regressions for each of the overconfidence proxies. In obtaining the results reported in this table, measurements of optimism, certainty, and self-reference are made universally without dividing up the fund manager reports into relevant sections.

⁴⁰ I 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. I am grateful to Prof. Abhayankar and Prof. Armitage for making this comment.

Table 17: Does fund-manager abnormal overconfidence impact subsequent mutual fund performance?

(Reports analysed universally)

This table displays the results of panel regressions of fund returns during the 2003-09 period using the four Carhart risk 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.). Two-tailed t-statistics are reported in brackets.

Variable	Optimism	Certainty	Self-reference	<i>Overconfidence</i> MetavARIABLE
Intercept	0.0065***	0.0059***	0.0062***	0.0075***
$R_M - R_F$	0.9452***	0.9447***	0.9473***	0.9366***
SMB	0.4236***	0.4242***	0.4239***	0.4350***
HML	0.4550***	0.4554***	0.4547***	0.4502***
MOM	-0.2092***	-0.2089***	-0.2085***	-0.2107***
Optimism	-0.1728 (-1.31)			
Certainty		0.0134 (1.06)		
Self-reference			-0.0759 (-1.27)	
<i>Overconfidence</i> MetavARIABLE				-0.0818 (-1.24)

As I established in section 7.3, it is important to select the correct parts of the annual report for content analysis purposes. The insignificant regression coefficients in Table 17 further confirm my expectation that one needs to divide up the reports into separate sections (*past performance discussion* and *fund outlook*) before performing the required textual analysis. Table 18 reiterates the same analysis with reports categorized by the above sections. 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.

Table 18: 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	<i>Overconfidence</i> 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)	
<i>Overconfidence</i> Metavariable				-0.4109* (-1.77)

It can be inferred from the results in Table 18 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 our expectation, which, I believe, may be due to the fact that fund managers commonly use a firm and resolute tone of voice in their reports to investors. This observation about the resoluteness of fund manager commentaries in general also comes across in the manual coding analysis performed in Chapter 5.

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, I substitute the prior one-year with the prior three-year OC scores in Table 19. Since SEC started filing mutual fund annual reports online in the Edgar database as of 2003, I have to start from 2005 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 19: 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	<i>Overconfidence</i> 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)	
<i>Overconfidence</i> 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, I look at a broader picture by including quintiles rather than deciles in my analysis. In the results reported in Table 20, 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 20: 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	<i>Overconfidence</i> 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)	
<i>Overconfidence</i> 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. I have investigated the 3-, 6-, and 9-month windows following the publication date of the annual report in Table 21.

Table 21: 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** (-2.05)	-0.5412** (-2.09)	-0.5661** (-2.14)
Certainty	0.1054* (1.67)	0.1021* (1.71)	0.1106* (1.78)
Self-reference	-0.2756* (-1.79)	-0.2812* (-1.88)	-0.3017** (-1.98)
<i>Overconfidence</i> metavariable	-0.4235* (-1.85)	-0.5027* (-1.92)	-0.4951** (-2.11)

The regression results reported in Table 21 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, I replicate the analysis using buy-and-hold returns instead of average monthly returns during the specified periods. However, I find that the regression results are not significantly different.

In a similar way, I test my 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, as can be seen in Table 22, and still suggest that abnormal levels of overconfidence can be detrimental to the fund's future investment performance.

Table 22: Does fund-manager abnormal overconfidence impact subsequent mutual fund performance?

(Inclusion of year fixed effects)

This table displays the results of panel regressions of buy-and-hold 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.

	Without year dummies	With year dummies
Optimism	-0.5194** (-1.98)	-0.5323* (-1.85)
Certainty	0.1125* (1.67)	0.1374 (1.41)
Self-reference	-0.2717* (-1.79)	-0.2919* (-1.70)
<i>Overconfidence</i> metavariable	-0.4109* (-1.77)	-0.3929* (-1.68)

The relationship between the performance of mutual funds and their investment styles is widely researched, as explained in chapter 2. To obtain a general perspective on the role of fund managers' overconfidence in this regard, I 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 23 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 23: 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	<i>Overconfidence</i> metavariable
Growth	-0.614** (-2.47)	0.1048* (1.65)	-0.3304* (-1.80)	-0.4575* (-1.79)
Value	-0.429* (-1.89)	0.1100 (1.51)	-0.2025* (-1.69)	-0.4233 (-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 fund managers possess better stock-selection skills than value-oriented managers. Can it be then posited that growth-oriented fund managers have similar

evidence of negative skill on the other side of the distribution? And could this be due their susceptibility to certain behavioural biases such as overconfidence? These questions obviously provide fertile ground for further empirical work in this area.

7.5 SUMMARY AND CONCLUSIONS

In the previous chapter, I demonstrated cross-sectional variations suggesting that good past performance boosts overconfidence as measured by all proxies used which is in line with theoretical expectations. In this chapter, I set out to investigate the dynamic relationship between fund managers overconfidence and the performance of their funds.

I 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 longing 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. Finally, it was 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.

CHAPTER 8 – CONCLUSIONS

8.1 INTRODUCTION

This chapter presents a summary of the findings made in this thesis and draws conclusions relevant to the proposed research questions. The implications of the research both for theory and practice as well as its limitations are discussed. Finally, suggestions for areas of future research are provided.

8.2 SUMMARY AND DISCUSSION

In this thesis, I developed and tested a model based on the theoretical contributions of Gervais and Odean (2001) and Choi and Lou (2008). This model explains the process by which financial agents become overconfident through learning about their own ability and past performance. While financial agents may not initially recognize their ability, in the course of time and with accumulating more experience, they attribute successful outcomes to their superior judgements, and failure to external factors or chance. Hence, financial agents “learn” to become overconfident through time. We also know that fund managers cannot outperform systematically better than chance, as the detailed review of literature in Chapter 2 illustrates. The question that arises is to what extent this effect may be due to the psychological factors influencing the process of investment decision making, as opposed to market characteristics.

In my empirical analysis, I test the hypothesis that excessive levels of overconfidence interfere with sound investment decision-making and thereby diminish future investment returns. In other words, everything else being equal, I expect a fund manager with higher levels of net overconfidence (after considering the effect of prior performance) to experience lower future returns. 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, excessive self-reference) as well as tone and readability, *ceteris paribus*.”

I used the well-known Carhart model as the base regression model to test my core research hypotheses. The Carhart (1997) model builds on the Fama-French three-factor model by adding prior-year momentum which, for the purpose of this research, adequately captures the effect of previous performance.⁴¹ 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. Hence, the term $\beta_{5i}E(OC_t)$ is added to the RHS of the Carhart model below. I use two empirical approaches to investigate this effect: the *portfolio-tracking* approach and the *calendar-time* method:

$$E(R_{it}) - R_{ft} = \beta_0 + \beta_{1i}[E(R_{mt}) - R_{ft}] + \beta_{2i}E(SMB_t) + \beta_{3i}E(HML_t) + \beta_{4i}E(MOM_t) \\ + \beta_{5i}OPTIMISM_{it} + \beta_{6i}CERTAINTY_{it} + \beta_{7i}SELF-REFERENCE_{it}$$

Several findings are explained in the thesis. 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 tend to have higher excess returns. Secondly, and more interestingly, the results indicate that holding the portfolio with the highest OPTIMISM scores leads to negative abnormal excess returns to the extent of around 0.84% per year (significant at the 10% level). The corresponding negative abnormal excess returns for CERTAINTY and SELF-

⁴¹ In discussions with Prof. Cuthbertson (Cass) and Prof. Taffler, it was agreed that a four-factor regression model such as Carhart should have adequate accuracy in studying the impact of fund manager psychological attributes on investment performance.

REFERENCE are, respectively, 1.56% and 0.36% per year. More broadly, alphas corresponding to the P4, P5 and P10 decile portfolios sorted on fund manager OPTIMISM as well as P5 and P6 in the case of CERTAINTY are significant at the 10% level.

Thirdly, a hedging strategy based on shorting funds with extremely overconfident managers and longing funds with normally (over)confident managers returns, on average, 2.88%. On the other hand, another hedging strategy based on shorting funds with extremely overconfident fund managers and longing funds with the least confident fund managers captures between 11 to 23 basis points per month based on the overconfidence proxy employed. In combination, the two strategies suggest an inverted U-shape relationship between overconfidence and performance. This relationship can be best displayed by plotting the portfolio-specific Carhart alphas for each of the overconfidence proxies, as displayed again in figure 22 below.

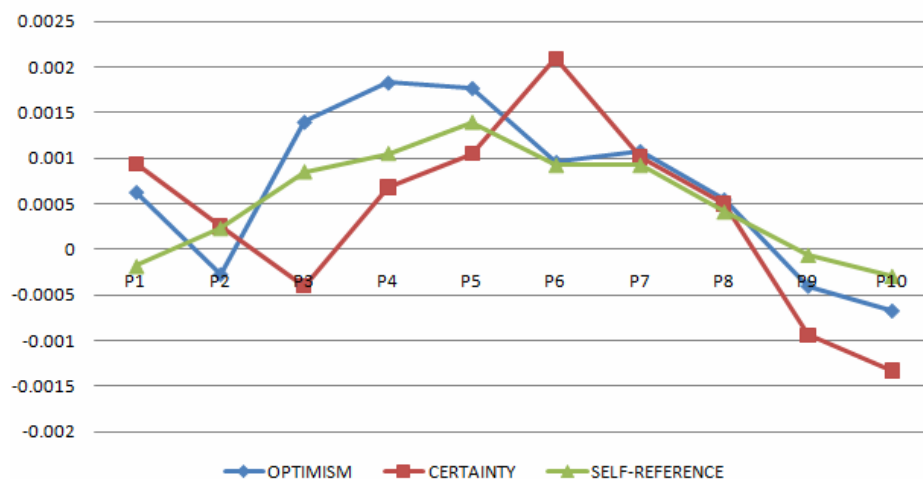


Figure 22: The effect of prior-year overconfidence on average abnormal excess returns (an inverted-U relationship)

(P10 is the annually ranked portfolio of funds with the highest overconfidence scores)

In chapters 5 and 6 of the thesis, I explored the effect of self-serving attribution bias among fund managers by analysing their reports in the light of their prior performance. What can be generally learnt, from the perspective of genre analysis

and corpus linguistics, is that fund managers write their reports in distinguishably different genres depending, among others, on their past performance record, their size and their investment style. My hypothesis regarding the existence of distinct rhetorical genres in fund manager reports is supported using a number of cross-sectional tests.

In addition, I established in a longitudinal study that the overall economic environment in which fund managers operate does influence the rhetoric of fund manager reports in aggregate. The results also provide support for the *Pollyanna* hypothesis; particularly among a number of categories such as loss-making funds (Table 1 is included at the end of this document as a representative example). For instance, the keywords “market” and “economy” are more frequently used among funds with negative absolute returns, and the least profitable funds in the positive return category. These observations seem to suggest that fund managers, in aggregate, refer to the market and the economy as external performance detractors in a self-serving way, which is consistent with the anecdotal evidence based on close-reading mutual funds. The frequency of use for “index” yields a similar conclusion, i.e. fund managers tend to make benchmark comparisons more frequently when performance is in the negative domain, and in doing so they strategically shift the reader’s attention away from the fact that they have, in fact, lost money by investing in the fund.

These findings, together with the evidence on readability, are consistent with the close-reading evidence also presented in the thesis. To a certain extent, one may be able to conclude that fund managers strategically adjust the overall tone and rhetoric of their reports in a self-serving way. However, it is equally plausible for this behaviour to stem from the unconscious psychological processes that may be in play in the minds of fund managers, since, as it is often demonstrated in this study, the underlying investment story can be an excellent sense-making implement for professional investors in general.

8.3 RESEARCH IMPLICATIONS

My 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 my 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, as described in chapter 2.

The results from the corpus-linguistic study of fund manager commentaries, which is another part of the thesis, demonstrate that the narrative section of mutual fund annual reports does have sufficient stability in patterns of usage to be considered a distinct genre of finance and accounting narrative. However, there is far less uniformity in the structure and contents of investment company annual reports compared to mainstream corporate annual reports (10-K). The precisely defined guidelines for preparing a 10-K report do not have an equivalent in the mutual fund industry. Given that investment companies can, in theory, use the flexible structure of the annual report as a vehicle for impression management incentives, there seems to be a strong case for demanding more regulation regarding investment company annual reports. Along similar lines, I believe that the SEC-proposed *Plain English* guidelines which came into force in 1998 should be made mandatory not only for prospectuses, but also for other investment company disclosures filed with the SEC including the annual report.

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.

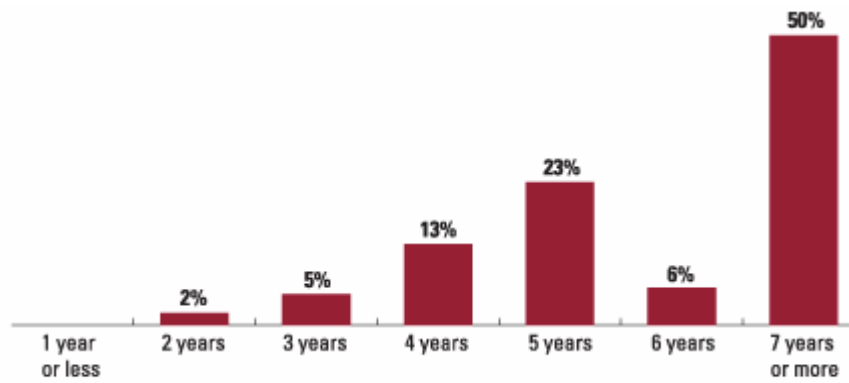
The investment industry as a whole, and fund trustees in particular, can also benefit by introducing some type of psychological screening in the fund manager selection process. The hiring of fund managers, in its traditional form, is heavily dependent on the manager's past performance record. In fact, a 2010 survey of US investment committees performed by a major investment house⁴² lists the top five factors influencing the hiring decision as:



Figure 23: Top five factors in hiring investment managers

The same survey reveals that the average length of fund manager retention in the industry is 5.8 years:

⁴² Vanguard Institutional Investors, the summary of survey results can be found at: [https://institutional.vanguard.com/VGApp/iip/site/institutional/researchcommentary/article?File=New sHireFire](https://institutional.vanguard.com/VGApp/iip/site/institutional/researchcommentary/article?File=New%20sHireFire)



Source: Vanguard, 2010.

Figure 24: Average length of relationship with an investment manager

Hence, hiring and firing decisions are highly important in the mutual fund industry. I 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.

The findings of this thesis can have important implications for fund rating companies. Currently, as explained in chapter 2, despite the power of fund ratings to influence asset flows in relation to mutual fund, there are doubts as to their predictive ability. In addition to the shortcomings pointed out by Amenc and Le Sourd (2005), fund rating systems have to deal with a number of other dilemmas. For example, while using broad categories to divide the funds into peer groups compromises accuracy, it is equally challenging to identify similar funds to be allocated to narrow groups. Moreover, in order to be able to properly classify funds, their portfolio

holdings need to be known throughout the whole evaluation period, which is not feasible most of the time.⁴³

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 new system need not replace existing ratings; rather it should help produce an alternative, more comprehensive rating methodology. Indeed, variables such as fund manager overconfidence can be added to existing performance-related metrics to enable an increased predictability of future investment returns.

8.4 RESEARCH LIMITATIONS

Empirical studies in accounting and finance, as in any other area of research, may have limitations in their scope and methods used, and by extension, in their results. This study uses novel methods in an emerging area of behavioural finance, and is therefore no exception in this regard. In this section, the research limitations known to the researcher are pointed out, and some areas for potential further research are identified.

8.4.1. LIMITATIONS RELATING TO CONTENT ANALYSIS AND THE DICTION PROGRAM

Content analysis as a research methodology has its own strengths and weaknesses. Fundamentally, content analysis is based on the assumption that the language people choose to express themselves in contains information about the nature of their

⁴³ Another issue concerns the identification of a fund's style. While the classification of a security along the value/growth continuum is neither objective nor stable, the fund manager's self-declared style can be equally misleading. For example, a style analysis on a sample of 748 funds performed by diBartolomeo and Witkowski (1997) demonstrates that 40% of the funds belong to a category other than the one declared. Similarly, Cooper, Gulen and Raghavendra Rau (2005) report that a significant number of mutual funds change their names only to benefit from the current hot investment styles. A year after such a name change, the fund experiences a 28% average cumulative abnormal flow, although no improvement in performance is made. Finally, Sensoy (2009) conducts a similar study that shows a mismatched size and value/growth benchmark is reported by about one third of actively-managed, diversified US equity mutual funds.

psychological states. A large body of literature on narrative analysis, both in psychology and more specifically in the area of accounting and finance, is built on this core assumption. The alternative assumption, however, is that environmental circumstances may shape verbal and written communication in a way that may render the underlying psychological states of individuals untraceable.

A potential weakness of large-scale computer-assisted content analysis is related to the computer programs used to analyse textual data. For example, most content analysis software packages such as DICTION rely on word frequencies and word categories to imply intended meaning. This approach, of course, is not perfectly accurate, yet it is a compromise that allows researchers to analyse large amounts of textual data in a practical way. To circumvent such problems, I have attempted, in chapter 5, to triangulate the results of computer-assisted analysis with manual coding and close-reading methodologies on a random sample of the annual reports studied in this thesis.

A few other points have to be made here. Firstly, any content analysis program has to deal with the issue of homographs. While DICTION has a built-in feature that enables it to make context-dependent judgements on homographs, and therefore is superior to most other comparable packages, human coding can obviously lead to more accurate results.

Secondly, DICTION makes use of pre-defined dictionaries which may not always be perfectly tuned to specific research needs. The program also allows user-defined dictionaries which clearly increase flexibility. Although the current study has not taken advantage of this feature, I believe that this should not have contributed to any significant inaccuracy since almost all of the fund rankings and comparisons performed are within sample, and therefore such biases should have mostly cancelled out in the process.

Thirdly, for each of the content analysis variables, DICTION specifies thresholds and declares values exceeding those thresholds as “out of range”, assuming a normal distribution for the underlying scores. While this is a useful feature, researchers should examine the distribution normality of the content analysis scores beforehand

(a step taken in this study). More importantly, DIRECTION thresholds are by definition static whereas, ideally, the researcher can improve the accuracy of the results by defining dynamic thresholds for time-series data depending on market environment and investor sentiment at any given observation date.⁴⁴

8.4.2. LIMITATIONS RELATING TO THE EMPIRICAL APPROACH

The findings in this thesis have to be interpreted with some level of caution. Given that the conceptual model proposed in Chapter 2 of the thesis eliminates certain contextual variables that are highly intangible and hence very difficult to quantify, correlations between psychological attributes and investment performance can be influenced by a number of potential confounding factors.

For instance, the organisational setting in which fund managers operate is only briefly described in Chapter 5. Further research can look at these organisational variables and more closely study their impact on fund manager behaviour. For example, it is valid to ask to what extent fund managers make investment decisions individually and/or to what extent their decisions are influenced by an overarching investment philosophy communicated by directors of the financial organisation. Equally, a more careful examination has to be made in relation to those funds that are run by a group of fund managers. One might wonder to what extent decision-making activities are shared in such funds, and how individual fund managers with potentially different investment ideas manage to influence the final investment outcomes. All of these questions provide fertile areas of future research.

With regard to empirical issues, I have used the calendar time method in part of the empirical analysis in this thesis. A word on the limitations of this approach is therefore necessary. The statistical robustness of the calendar time analysis comes at a cost. The calendar time approach is restricted to analysing a single, binary investor characteristic (Hoechle, Schmid and Zimmerman, 2009). Although it is sometimes possible to segregate investors or firms naturally into two clear-cut groups such as men and women (e.g., Barber and Odean, 2001), some research questions require the

⁴⁴ I am grateful to Dr. Lucy Liu for making this comment.

researcher to analyse continuous or multivariate investor or firm characteristics. Researchers often circumvent this limitation, as is done here, by first segregating investors into sub-groups, such as deciles or quintiles, and then measuring the performance for each of these sub-groups independently based on the calendar time approach.

However, such portfolio-rankings have a number of drawbacks. Hoechle et al explain that due to the lack of a natural grouping criterion, the resulting group definitions may be somewhat arbitrary, and an analysis based on this method has to be limited to only a few investor characteristics in order for the number of sub-groups not to become too numerous. In addition, it may be challenging to fully interpret the statistical results of an analysis based on portfolio sorts and, therefore, for simplicity, statistical inference is often based on comparing top and bottom sub-groups.

The Carhart four-factor model, which is the core asset pricing model used in this study, is of course not without some weaknesses in certain applications. While the momentum factor is an important addition to the Fama-French three factor model, in essence, it consists of a persistence test. Fama and French (2010) argue that testing for persistence in fund returns, i.e. whether past winners continue to outperform and losers continue to underperform, is not a suitable approach to distinguishing skill from luck. While this thesis does not seek to enter the skill versus luck debate, it is worth pointing out that persistence tests often rank funds on short-term past performance, and therefore there may be little evidence of persistence since the allocation of funds to winner and loser portfolios is largely based on noise. The alternative approach used in more sophisticated empirical studies of performance measurement, as in Fama and French (2010), consists of using long histories of individual fund returns together with bootstrap simulations of return histories in order to infer the existence of superior and inferior funds.

8.5. AREAS OF FURTHER RESEARCH

A potentially rich area for further research in the context of this thesis 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.

Overconfident fund managers can be classified in a number of ways as explained in section 2.5 of the thesis. This depends, among others, on how overconfidence is defined and measured in the first place. In this study, I focus, to some extent, on the value/growth distinction. However, one can equally examine passive fund managers as a control group for the main study. In other words, if we hold onto the thesis that overconfidence develops through active investment decision-making, we can normalize the overconfidence measures using any observation of this variable in

passive managers. That is to say, any given fund manager is only overconfident by as much as his or her measured overconfidence level exceeds that of an equivalent passive fund manager. Since I have initially excluded passive fund managers from my study sample, this approach was not chosen in the thesis. However, it can clearly provide an interesting area for further research.

With regards to hedge funds, measuring overconfidence following the methods used in this study can prove challenging since it is quite difficult to access hedge fund manager reports in any systematic way. Hedge funds, compared to mutual funds, are not as transparent in reporting to their investors. In addition, hedge funds are subject to far less stringent SEC disclosure requirements. However, assuming that data access issues are resolved, hedge funds can provide a fertile ground for study of manager reports. This is because hedge fund managers are supposedly less restricted in writing to their clients as their reports are not reflected in the public domain. Hence, one may argue that hedge fund reports can provide more traction for inferring psychological attributes from narratives.

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.

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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APPENDICES

APPENDIX 1: AN EXAMPLE OF FUND MANAGER COMMENTARIES STUDIED

The financial statements that make up the Annual Report give us an opportunity to review what has happened and give insight into what may happen. For the twelve months ending September 30th, 2009, the Growth & Income Fund was up 8.64%. This compares favorably with the S&P Index down 5.91% for the same period.

In preparing to write this letter, I review the previous year's letter to note what concerns were driving the markets at that time. September 30th, 2008 the financial meltdown was intensifying and accelerating. Peeling back the financial onion revealed numerous economic short-comings. Once the finger pointing began, it was obvious who was to blame – everyone. Greedy Wall Street, consumers lying on mortgage applications, real estate speculators, bankers that didn't know the first thing about banking, regulators "in bed" with those they were regulating, a Department of Treasury bought and paid for by the hedge fund industry, and the likes of Goldman Sachs. Additionally, "challenged" regulators ignored abusive trading practices and couldn't catch Ponzi king Bernie Madoff even when his shenanigans were presented to them on a silver platter.

The markets continued their free fall for the next six months but by March the stock market had reached an emotional low point. The financial meltdown of 2008-09 had established itself firmly in the history books as a true financial crisis. Fear, panic and then capitulation created a classic buying opportunity. Our Elite Growth & Income Fund declined more severely than most funds but we did correctly anticipate that the financial crisis was not the end of the world. We positioned our portfolio to take advantage of Government recovery programs and the subsequently expected stock market rally. For the next six months from March to the end of the fiscal year (September 30th,) the stock market and our Elite Growth & Income Fund had significant recoveries. As indicated earlier, the Growth & Income Fund was up 8.64% for our fiscal year while the stock market was still in negative territory.

The obvious question is; where do we go from here? As I indicated in my last shareholder letter, we believe it would be prudent to strike a note of caution. The recovery from the March lows have been significant but to assume the advance will continue unabated would be a mistake. In reviewing the enclosed Annual Report, you will see that we hold a large part of our portfolio in cash, in the form of Treasury Bill investments. We also have dedicated funds to health care, believing the confusion surrounding healthcare issues have depressed healthcare stocks creating a great investment opportunity. We are also staying with our investments in financial stocks, specifically insurance stocks. For the new fiscal year, I believe we have positioned our portfolio to capture the appreciation potential in a number of undervalued investments. Our large cash position allows us the flexibility to seize investment opportunities if the stock market were to have a significant decline or correction. We look forward to the new fiscal year and believe it will be rewarding.

APPENDIX 2: DEFINITIONS OF DICTION VARIABLES USED IN OPTIMISM AND CERTAINTY MASTER VARIABLES

(Source: Diction 5.0 User's Manual)

TENACITY: All uses of the verb to be (*is, am, will, shall*), three definitive verb forms (*has, must, do*) and their variants, as well as all associated contraction's (*he'll, they've, ain't*). These verbs connote confidence and totality.

LEVELING: Words used to ignore individual differences and to build a sense of completeness and assurance. Included are totalizing terms (*everybody, anyone, each, fully*), adverbs of permanence (*always, completely, inevitably, consistently*), and resolute adjectives (*unconditional, consummate, absolute, open-and-shut*).

COLLECTIVES: Singular nouns connoting plurality that function to decrease specificity. These words reflect a dependence on categorical modes of thought. Included are social groupings (*crowd, choir, team, humanity*), task groups (*army, congress, legislature, staff*) and geographical entities (*county, world, kingdom, re public*).

INSISTENCE: This is a measure of code-restriction and semantic contentedness. The assumption is that repetition of key terms indicates a preference for a limited, ordered world. In calculating the measure, all words occurring three or more times that function as nouns or noun-derived adjectives are identified (either cybernetically or with the user's assistance) and the following calculation performed: [Number of Eligible Words x Sum of their Occurrences] ÷ 10. (For small input files, high frequency terms used two or more times are used in the calculation).

NUMERICAL TERMS: Any sum, date, or product specifying the facts in a given case. This dictionary treats each isolated integer as a single word and each separate group of integers as a single word. In addition, the dictionary contains common numbers in lexical format (*one, tenfold, hundred, zero*) as well as terms indicating numerical operations (*subtract, divide, multiply, percentage*) and quantitative topics (*digitize, tally, mathematics*). The presumption is that Numerical Terms hyper -specify a claim, thus detracting from its universality.

AMBIVALENCE: Words expressing hesitation or uncertainty, implying a speaker's inability or unwillingness to commit to the verbalization being made. Included are hedges (*allegedly, perhaps, might*), statements of inexactness (*almost, approximate, vague, somewhere*) and confusion (*baffled,*

puzzling, hesitate). Also included are words of restrained possibility (*could, would, he'd*) and mystery (*dilemma, guess, suppose, seems*).

SELF-REFERENCE: All first-person references, including *I, I'd, I'll, I'm, I've, me, mine, my, myself*. Self-references are treated as acts of indexing whereby the locus of action appears to reside in the speaker and not in the world at large (thereby implicitly acknowledging the speaker's limited vision).

VARIETY: This measure conforms to Wendell Johnson's (1946) Type-Token Ratio which divides the number of different words in a passage by the passage's total words. A high score indicates a speaker's avoidance of overstatement and a preference for precise, molecular statements.

PRAISE: Affirmations of some person, group, or abstract entity. Included are terms isolating important social qualities (*dear, delightful, witty*), physical qualities (*mighty, handsome, beautiful*), intellectual qualities (*shrewd, bright, vigilant, reasonable*), entrepreneurial qualities (*successful, conscientious, renowned*), and moral qualities (*faithful, good, noble*). All terms in this dictionary are adjectives.

SATISFACTION: Terms associated with positive affective states (*cheerful, passionate, happiness*), with moments of undiminished joy (*thanks, smile, welcome*) and pleasurable diversion (*excited, fun, lucky*), or with moments of triumph (*celebrating, pride, auspicious*). Also included are words of nurturance: *healing, encourage, secure, relieved*.

INSPIRATION: Abstract virtues deserving of universal respect. Most of the terms in this dictionary are nouns isolating desirable moral qualities (*faith, honesty, self-sacrifice, virtue*) as well as attractive personal qualities (*courage, dedication, wisdom, mercy*). Social and political ideals are also included: *patriotism, success, education, justice*.

BLAME: Terms designating social inappropriateness (*mean, naive, sloppy, stupid*) as well as downright evil (*fascist, blood-thirsty, repugnant, malicious*) compose this dictionary. In addition, adjectives describing unfortunate circumstances (*bankrupt, rash, morbid, embarrassing*) or unplanned vicissitudes (*weary, nervous, painful, detrimental*) are included. The dictionary also contains outright denigrations: *cruel, illegitimate, offensive, miserly*.

HARDSHIP: This dictionary contains natural disasters (*earthquake, starvation, tornado, pollution*), hostile actions (*killers, bankruptcy, enemies, vices*) and censurable human behaviour (*infidelity, despots, betrayal*). It also includes unsavoury political outcomes (*injustice, slavery, exploitation*,

rebellion) as well as normal human fears (*grief, unemployment, died, apprehension*) and in capacities (*error, cop-outs, weakness*).

DENIAL: A dictionary consisting of standard negative contractions (*aren't, shouldn't, don't*), negative functions words (*nor, not, nay*), and terms designating null sets (*nothing, nobody, none*).

ACCOMPLISHMENT: Words expressing task-completion (*establish, finish, influence, proceed*) and organized human behaviour (*motivated, influence, leader, manage*). Includes capitalistic terms (*buy, produce, employees, sell*), modes of expansion (*grow, increase, generate, construction*) and general functionality (*handling, strengthen, succeed, outputs*). Also included is programmatic language: *agenda, enacted, working, leadership*.

APPENDIX 3: A SELECTION OF SCHOLARLY RESEARCH USING THE DICTION
5.0 SOFTWARE

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APPENDIX 4: THE JAVA PROGRAM USED TO EXTRACT MUTUAL FUND ANNUAL REPORTS FROM EDGAR

The following is a simple Java code I developed in collaboration with Dr. Mark Greenwood (Manchester Business School) that can be used to read a large number of webpages with known URLs and save them in a desired location. The program can also choose to save an alternative URL if the first address is invalid or missing data.

```
// URLreader.java
// java.sun.com/docs/books/tutorial/...
import java.net.*;
import java.io.*;
public class MultURLfiler3
{
    FileInputStream fis = null;
    FileInputStream fi2s = null;
    FileInputStream fws = null;
    FileOutputStream fos = null;
    FileOutputStream fes = null;
    PrintWriter err = null;
    boolean URLtester (String givenURL)
    {
        try {
            URL url = new URL( givenURL );

            BufferedReader in = new BufferedReader(
                new InputStreamReader(
                    url.openStream() ));
            String inputLine;
            // Test reading data from URL
```

```

        inputLine = in.readLine();
        in.close();
        return true;
    }
    catch (MalformedURLException e) {
        System.out.println("URL problem " + e);
        err.println("URL problem " + e);
        err.println(givenURL);
        return false;
    }
    catch (IOException e2) {
        System.out.println( "IOException tester " + e2 );
        err.println("IOException " + e2 );
        err.println(givenURL);
        return false;
    }
}

void URLfiler (String givenURL, String fname)
{
    try {
        URL url = new URL( givenURL );
        fos = new FileOutputStream( fname );
        BufferedReader in = new BufferedReader(
            new InputStreamReader(
                url.openStream() ));
        PrintWriter out = new PrintWriter(fos);
        String inputLine;
        while ((inputLine = in.readLine()) != null)
            out.println( inputLine );
        in.close();
        out.close();
    }
}

```



```

    }
    catch (MalformedURLException e) {
        System.out.println("URL problem " + e);
        err.println("URL problem " + e );
        err.println(givenURL);
    }
    catch (IOException e2) {
        System.out.println( "IOException filer " + e2 );
        err.println("IOException " + e2 );
        err.println(givenURL);
    }
}

public MultURLfiler3 (String fnameurl, String fnameout, String alturl)
{
    // this.theURL = givenURL;
    try {
        fis = new FileInputStream(new File(fnameurl) );
        fws = new FileOutputStream(new File(fnameout) );
        fi2s = new FileInputStream(new File(alturl) );
        fos = new FileOutputStream("testout.txt");
        fes = new FileOutputStream("errors.txt");
        //Object content = urlcon.getContent();
        //System.out.println(content);

        BufferedReader in = new BufferedReader(
            new InputStreamReader(
                fis ));

        BufferedReader in2 = new BufferedReader(
            new InputStreamReader(
                fws ));

        BufferedReader in3 = new BufferedReader(
            new InputStreamReader(

```

```

        fi2s ));

PrintWriter out = new PrintWriter(fos);
err = new PrintWriter(fes);
String inputLine1, inputLine2, inputLine3 ;

while ((inputLine1 = in.readLine()) != null) {
    inputLine2 = in2.readLine();
    inputLine3 = in3.readLine();
    if ( URLtester(inputLine1) ){
        out.println( "Copy " + inputLine1 + " to " + inputLine2 );
        System.out.println( "Copy " + inputLine1 + " to " + inputLine2 );
        URLfiler( inputLine1, inputLine2 );
    }
    else {
        out.println( "Copy " + inputLine3 + " to indx" + inputLine2 );
        System.out.println( "Copy " + inputLine3 + " to indx" + inputLine2 );
        URLfiler( inputLine3, "indx" + inputLine2 );
    }
};
in.close();
in2.close();
in3.close();
out.close();
err.close();
}
catch (IOException e2) {
    System.out.println( "IOException " + e2 );
    err.println("IOException main" + e2 );
    err.println(fnameurl);
}
}

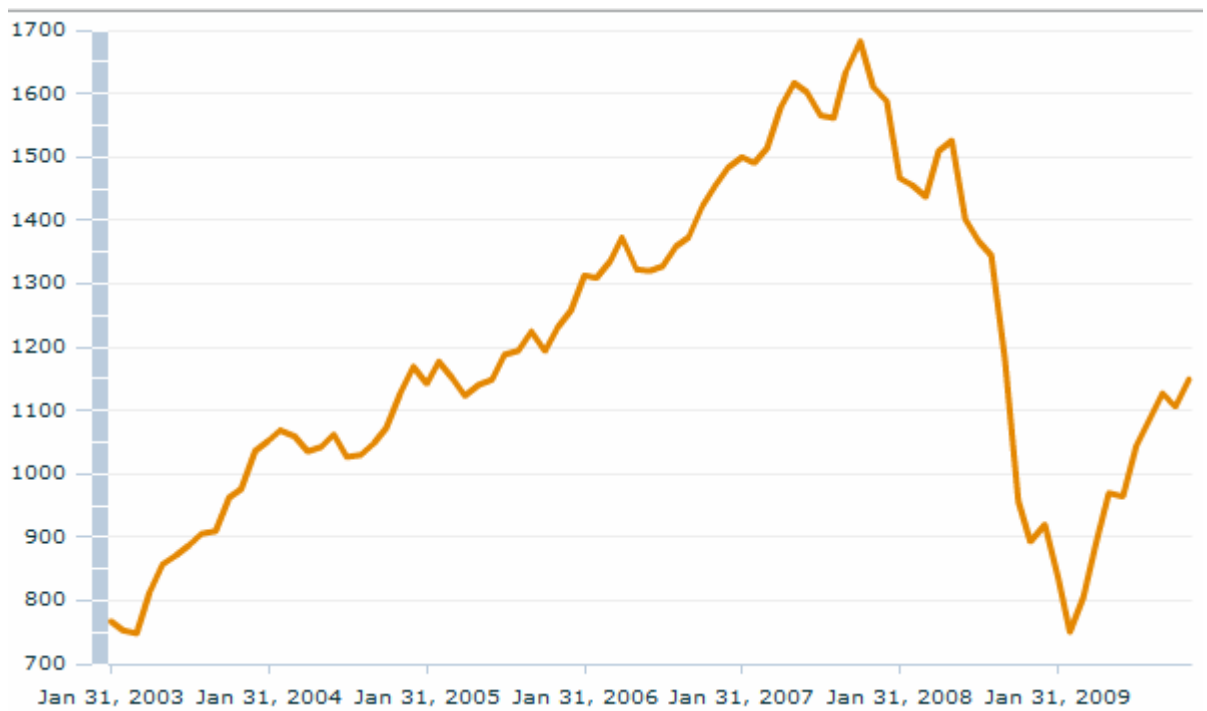
```

```
public static void main (String[] args) {  
    System.out.println( "start" );  
    System.out.println( args[0] + " - " + args[1] + " alt " + args[2] );  
    new MultURLfiler3( args[0], args[1], args[2] );  
    System.out.println( "finish" );  
}
```

APPENDIX 5: LEADING EQUITY MARKET INDICES PROXYING FOR ECONOMIC CONDITIONS DURING THE STUDY PERIOD



S&P 500 (source: Google Finance)



MSCI World (source: MSCI Barra)

APPENDIX 6: LEGALESE AND INDUSTRY JARGONS USED TO COMPUTE THE
PLAIN ENGLISH READABILITY MEASURE

Source: SEC Staff Legal Bulletin at <http://www.sec.gov/interp/leg/cfs1b7a.htm>

Jargon/technical terms

proprietary drug
intravenous solutions
logistics capabilities
coordinated manufacturing
and distribution efforts
proprietary medicines
vertically integrated cost-
efficient providers
revenue synergies
lower margin
products utilization realigning
sales forces
centralized management
information systems
profit-enhancing synergies
global platform

Legalese

definitive agreement
consummation
those preceded by
herein
set forth under
by such forward-
looking statements
without limitations
cease to conduct
completion of the
combination
commencing
hereinafter so
surrendered
defeased
as amended
qualified in its entirety