The relationship among underdog bias, self-rated performance and personal risk propensity

Exploring how our past experiences influence how we see ourselves and the decisions we make

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Abstract

Individuals are affected by different biases and heuristics in different ways. This dissertation explores the two of these (underdog bias and self-rated performance) and their relationship with personal risk propensity in the South African investment professional community.

To measure risk propensity in investment professionals, a new instrument was developed. This was tested against a risk measurement scale based on the original work in prospect theory. Both risk propensity measures found similar and comparable results in the investment professionals, and similar results when compared to other studies that studied risk propensity in a more general population and risk tolerance in investment professionals in Europe.

Similarly, self-rated performance had comparable results to other studies on overconfidence bias and the better than average effect. Investment professionals, on average, think that they are better than their average peer.

Underdog bias, or the headwinds/tailwinds asymmetry, had an unexpected result where the investment professionals felt they did not suffer from stronger headwinds and barriers compared to their peers. This was an unexpected result and may show that the South African investment industry feel more grateful than others to be where they are or, the sample may have triggered the boundary condition of underdog bias where individuals feel their personalised benefits more than their shared headwinds. Further testing is required in the same population as well as similar populations to confirm the boundary condition.

The three constructs were tested to understand the relationship between them. In each of the three cases, there was no significant relationship between any of the constructs. The results were different to what was expected and, subject to further testing, may have found a blind spot in investment professionals where they believe that what when they are doing something they consider to be right, they do not perceive the increased risks associated with the action. These blind spots have an impact on how risk is managed investment firms and needs to be monitored to protect the overall firm.

Keywords: Underdog Bias, Headwinds/Tailwinds Asymmetry, Self-rated Performance, Risk Propensity

Declaration

I declare that this research project is my own work. It is submitted in partial fulfilment of the requirements for the degree of Master of Business Administration at the Gordon Institute of Business Science, University of Pretoria. It has not been submitted before for any degree or examination in any other University. I further declare that I have obtained the necessary authorisation and consent to carry out this research.

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Contents

List of Figures

List of Tables

1 Review of the Topic

1.1 Decoding the Title

The paper wishes to determine if there are relationships among underdog bias (personalised experiences of the past) (Davidai & Gilovich, 2016; Tversky & Kahneman, 1973), self-rated performance (confidence in an individual's abilities) (Guenther & Alicke, 2010; Ross & Sicoly, 1979), and personal risk propensity (the amount of risk that an individual is willing to take) (Hoffmann, Post, & Pennings, 2015; Kahneman & Tversky, 1979). The three constructs will be tested to understand if there is a relationship between them to determine if an individual's experiences can influence their personal perceptions and their decisions.

1.1.1 Underdog Bias Definition

Each individual has to overcome different types of events or experiences to get to the position they are in currently. Davidai and Gilovich (2016) argue that individuals remember the headwinds they face more than the tailwinds that support them, giving people a sense that they have had to overcome more than what they have been blessed with. "The barriers and hindrances command attention because they have to be overcome; benefits and resources can often be simply enjoyed and largely ignored" (Davidai & Gilovich, 2016, p. 835). The difference in recall of the things that hinder us and the things that help us create the headwind/tailwind asymmetry, or the defining condition of underdog bias that individuals, on average, feel that they have had to overcome more than what others have had to, to get to the same place.

1.1.2 Self-Rated Performance Definition

Festinger (1954) in his paper on social comparison theory determined that people have an instinctual drive to evaluate themselves, to take stock of how good they are. This can be determined by using a non-social means, for example, if someone can pick up a particular heavy object. However, in most situations, it is difficult to assess oneself accurately as no non-social means of evaluation are available. It is in these situations that "people evaluate their opinions and abilities by comparison respectively with the opinions and abilities of others" (Festinger, 1954, p.118). It is this rating of an individual's abilities that defines self-rated performance. The individual's perception of their own abilities and performance in comparison to their assessment of the average person's abilities in their peer group.

1.1.3 Personal Risk Propensity Definition

Kahneman and Tversky (1979) in their paper on prospect theory showed that individuals do not always follow the rational expected outcome for a particular set of choices. They often prefer to take a sure thing in a gain (being risk averse) and are risk seeking when facing a potential loss.

The level that individuals are risk seeking versus risk adverse is different depending on the situation and the natural level of risk in the individual (Iqbal, 2013). It has been tested to be (on average) anywhere between 1.5 and 2.5 in the gain to loss ratio (Kahneman & Lovallo, 1993). This natural or base level of risk is what defines personal risk propensity.

1.2 Overview of the Study

Economic theory has historically been used to predict human behaviour. The basis for prediction has been that individuals are rational agents that are self-interested and predictable (Baye & Prince, 2013). In practice, this does not necessarily apply (Kahneman, 2011; Rabin & Thaler, 2001).

Based on the rationality assumption the von Neumann-Morgenstern expected utility hypothesis was developed. It provides a simple model that can predict what the rational agent will do when evaluating different options (Iqbal, 2013). The problem is that people are not always rational and have been found to be consistently irrational in certain situations (Rabin & Thaler, 2001).

To explain the irrationality (or unpredictability) of people in their decision making, psychologists and behavioural economists have developed many different mechanisms and theories. Stanovich and West (2000) argued that one of the reasons that individuals not consistently rational is because they use different methods of thinking to come to their conclusions. The first type or system of thinking (termed System 1) is the more natural or automatic way of thinking. It is quick, requires limited energy and is almost automatic in nature. The second system (System 2) is more deliberate and is a much more energy taxing (and thus less efficient) method.

The automatic nature of System 1 thinking can lead to individuals using heuristics (shortcuts) in their different approaches to solving problems or perceiving the world around them. A heuristic is merely a rule (or method that System 1 employs) that allows people to change difficult problems into simpler more understandable ones (Slovic, Fischhoff, Lichtenstein, & Roe, 1981). These heuristics can be useful in everyday life as they save energy by using

System 1 but these shortcuts can lead to individuals being instinctually influenced by salient memories, recent events or external impressions from others, creating cognitive biases (Kahneman, 2011).

The heuristics and cognitive biases that influence individuals come in many different forms. The availability heuristic describes how individuals are influenced by their recent experiences as those memories are more salient than others (Tversky & Kahneman, 1973). The same heuristic creates a shortcut in thinking where individuals will answer a question or problem based on how they “know” the world to be, ignoring the base rates that occur in the general population.

Cohen and Cohen (1984) gave an interesting example in their paper where they coined the phrase the “clinician’s illusion”. The team found that clinician’s (and the public) held the view that “opiate addiction was an incurable state for most if not all users” (p.1179), but a study on heroin addicted Vietnam veterans found that 71% were drug free after two and a half years without seeking formal help. What Cohen and Cohen (1984) found was that the clinicians’ that dealt with extreme cases of people who were seeking help and needed help, but their sample excluded those that managed to remove themselves from the substance dependency themselves, skewing their view on the addiction through the availability heuristic.

The availability heuristic is the basis of underdog bias which describes how a person recalls the experiences that they have overcome more saliently than the factors that have enabled them to get to their current situation (Davidai & Gilovich, 2016). This creates a meaningful sense in individuals that they have had to overcome more than their peers to get to where they are, making the individual the underdog in their own story. Additionally, this forms an important part of the factors that influence self-rated performance. Other biases that influence self-rated performance are egocentric bias (Ross & Sicoly, 1979), hindsight bias (Agans & Shaffer, 1994), and optimism bias (Lovallo & Kahneman, 2003).

Inflated self-rate performance, overconfidence and the better than average effect can cause individuals to overvalue their contribution to teams (Schroeder, Caruso, & Epley, 2016) and to overstate their skill set when compared to others (Guenther & Alicke, 2010).

This inflated self-rated performance forms one half of the two main determinants of risk perception in individuals, the other factor is the availability heuristic. An individual’s risk perception requires some subjectivity to be taken into account when determining the “value” of risks. This subjectivity is influenced by information (availability heuristic) as well as the individual's belief in their ability to mitigate that risk (overconfidence). The subjectivity of the analysis of the risk leaves individuals open to biases influencing their perception of specific risks (Slovic et al., 1981).

Risk perception does not necessarily equate to the level of risk people will take on, or their propensity for risk. Kahneman and Tversky (1979), through prospect theory, described that people tend to be risk averse when facing gains but are risk seeking when facing losses. This difference in risk perception leads to a loss aversion ratio, where individuals need between a 1.5 and 2.5 gain versus loss to take on a specific risky proposition (Novemsky & Kahneman, 2005).

The three constructs – underdog bias (Davidai & Gilovich, 2016), self-rated performance (Williams & Gilovich, 2008) and personal risk propensity (Kahneman & Tversky, 1979) – have been studied individually and in some cases (like the tacit link between underdog bias and self-rated performance, and overconfidence and risk perception) indirectly together (Davidai & Gilovich, 2016; Kahneman & Lovallo, 1993). What has not been studied is if underdog bias may be a factor in predicting self-rated performance, and if self-rated performance or underdog bias is a factor in predicting personal risk propensity.

1.3 Business Needs for the Study

Although business is not an individual, businesses are made up of a group of individuals that influence the actions of a business. In one of his motivational talks, Zig Ziglar, was credited with the saying, "You don't build a business. You build people" (Ziglar, 2016). Although this was meant to push management to focus on people to drive sales, it shows the importance that a business is not a unique being it is the sum of all the people that are part of the business.

The same people that need to make decisions in those businesses are empowered by shareholders and customers (in the investment environment) to be the custodians of value for them. As the custodians of value those stakeholders expect that the decision makers in business will mitigate the potential risk to a level that is acceptable for the potential reward.

In reality, people (as a group) do not have a consistent attitude towards risk, thus it is very difficult to determine if people will predominantly be risk seeking or risk adverse as a population (Iqbal, 2013). In individuals, it has been tested that there is a variable level of risk that currently exists as the loss aversion ratio tends to shift between 1.5 and 2.5 depending on the reference point (Novemsky & Kahneman, 2005). People have different levels of natural risk propensity regardless of what the circumstances are (King & Slovic, 2014). This makes it very difficult for investment businesses to match the professionals with their customers without doing some level of testing – which to the researcher’s knowledge is not happening in the South African investment industry.

Instead, the South African investment industry uses the structure of the investments (the portion invested in local and foreign equities, bonds, property and cash) of collective schemes to determine risk (ASISA, 2017). For private investment portfolios, the system is replaced by the gut feel for acceptable risk the professional thinks the customer wants. Neither of these two systems provides a match between the risk that the customer wants to take and the natural risk propensity the investment professional is likely to tend toward.

If a business can successfully match investment professionals with investors correctly, it will enable the specific businesses to fulfil the needs of individual investors to a better degree than the current status quo. This makes it important from a business perspective to understand which individual professionals have a higher risk propensity and if there are other measures like their past (underdog bias) or perhaps their perception of themselves (self-rated performance) that influence their risk propensity.

By understanding the risk propensity levels that exist in decision makers of a business, the leadership of the business will be able to match the individual professional investors to the more risk seeking customers. This will create a better match for the customers, shareholders and the professionals.

1.4 Theoretical Need for the Study

Heuristics and biases have been a well-documented subject as behavioural economists and psychologists have attempted to explain the difference between normative models and descriptive human behaviour (Stanovich & West, 2000).

This has led to the understanding of different types of bias and heuristic constructs that we see in the literature today. Higher order heuristics, like availability, have been studied as factors that lead to other cognitive biases (Tversky & Kahneman, 1973).

Underdog bias and self-rated performance (or overconfidence bias) both find their roots in availability bias. Together those biases (underdog and availability bias) have been found to be important factors in risk perception (Slovic et al., 1981).

But what has not been studied is if these factors play an important part in individual risk propensity. If risk propensity is influenced by either underdog bias or self-rated performance, it may help explain why, or what factors influence, people when they take on excessive risk, or why people are risk averse. Therefore this study will attempt to shed new light on personal risk propensity and its potential relationship between underdog bias and self-rated performance.

1.5 Research Scope

The research will focus on investment professionals that are currently involved in investment decisions within their firms. The risk propensity of these individuals is seen as significant as not only do they have to deal with risk mitigation whenever they review their decisions but they also typically have a level of risk that they communicate to their customers for the type of fund they propose to invest in (Hoffmann et al., 2015).

The research will focus on testing underdog bias, self-rated performance and risk propensity exclusively.

1.6 Purpose of the Study

Personal risk propensity plays an important role in matching an individual to a specific business objective. Although an individual may temper their risk there is a level of natural risk propensity that is part of the makeup of that person (Novemsky & Kahneman, 2005).

The principal objective of the study will be to determine if underdog bias and self-rated performance influence personal risk propensity. This will enable business to match an individual investment professional to the right level of expected risk of the investor or fund.

Although this study is targeted at individuals in the investment community, it may be expanded to include all business that need to match the level of risk of their employees to their offering. For example, a business that requires a safety engineer may want to understand that individual’s level of risk propensity.

Specific sub-objectives of the study include:

a) Understand the level of underdog bias (Davidai & Gilovich, 2016) that exists within the investment community.
b) Understand the level of self-rated performance (Williams & Gilovich, 2008) that exists within the investment community and what that level of overconfidence is compared to the current average that exists in literature.

c) Understand the different levels of risk propensity (Kahneman & Tversky, 1979) that exists in the investment community using a new scale and risk propensity measurement scale based on prospect theory.
    i. Test and analyse the validity of the new personal risk propensity scale.
    ii. Understand the different or similar outcomes to the risk propensity outcomes from the prospect theory scale.

d) Provide screening or testing recommendations to potential businesses that require the matching of risk propensity to specific job roles.

1.7 Outline of the Study

The structure of the rest of the study starts with a review of the existing academic literature, focussing on the three key components of the study. Starting with underdog bias, then self-rated performance and ending with the individual risk propensity. There will then be a review of what is known and what is unknown.

Chapter three will illustrate the three hypotheses of the research.

Chapter four is an outline of the methodology used in the study.

Chapter five will present the results of the study.

Chapter six will go into a discussion of the results of the study.

Chapter seven will conclude the overall study.

2 Literature Review

2.1 Introduction

The three constructs of underdog bias, self-rated perception and personal risk propensity have their roots in behavioural economics (Davidai & Gilovich, 2016; Kahneman & Tversky, 1979; Kahneman, 2011; Schroeder et al., 2016). This makes the constructs related, but they all have their individual properties.

This literature review starts by exploring the different systems of thinking that determine how our environment affects the way that individuals perceive the world (Stanovich & West, 2000). This is then followed by an explanation of heuristics and biases with an in-depth review of availability bias and the Tversky and Kahneman (1973) seminal paper on the subject.

The dissertation then takes a deeper look at the existing literature on underdog bias, self-rated performance and risk perception as well as describing the different factors that create the different constructs.

The final construct of risk propensity is then reviewed to develop an understanding of risk aversion and prospect theory. A minor examination is carried out on the underlying differences between prospect theory and expected utility theory. This examination shows that the base of economic theory (rational agency) does not always apply in reality, resulting in risk propensity being measured in a different way than purely the best probable outcome (Kahneman & Tversky, 1979).

The dissertation then pulls together the different existing theory of all three constructs before proposing the three different hypotheses that are going to be tested in the field research.

2.2 Bounded Rationality and System 1 & 2 Thinking

Economic theory has been based on the premise of the existence of the rational person that has tastes that do not change and acts in their best interests always (they are selfish). This has allowed economists to predict that if a person likes bananas more than apples and apples more than pears, then the rational person can be considered to prefer bananas more than apples – known as the von Neumann-Morgenstern utility function (Baye & Prince, 2013; Iqbal, 2013). Economists realise that this could not be possible for all consumption of bananas as people may start to prefer apples when they have had their 100th banana, or perhaps they decide that an apple may be better tasting one day. This realisation was the basis of the development of the marginal utility function (by Swiss scientist Bernoulli when he explained the problem that his cousin had presented in the St Petersburg paradox (Kahneman, 2011)).

Psychologists have been aware of diminishing returns or at least it psychological twin Feschner's law that describes how the starting point of an action determines how it is perceived (Nutter, 2010). An easy way to think of how Feschner's Law works is through the example of putting your cold hand in room temperature water has a different effect than putting a hot hand in room temperature water. The one feels hot and the other cold. However, they are the same. Fechner's law points out that any action or change needs to be perceived from a reference point.

Even with the law of diminishing returns, in both economics and psychology, the outcomes of all events are still determined by a rational being. This has been challenged, and it has been proven time and time again that people tend to deviate from the models described by Feschenr's law and von Neumann-Morgenstern's utility function (Stanovich & West, 2000).

Stanovich and West (2000) confirm that people's responses deviate from standard models as they "assess probability incorrectly, they test hypotheses inefficiently, they violate the axioms of utility theory, they do not properly calibrate degrees of belief, they over-project their own opinions on others, they allow prior knowledge to become implicated in deductive reasoning" (p.645). To explain this problem Stanovich and West (2000) proposed two different styles of thinking that allow people to analyse problems in different ways, termed System 1 and System 2 (for a review of dual-processing reasoning see Evans (2008)).

System 1 thinking is the unconscious level of thinking. It requires limited computational capacity (and thus, energy) and can give an answer to the person questioning the thought before they understand where that answer came. It is instinctual, immediate and the default style of thinking. It is also known as interactional intelligence or the adaptive unconscious (Evans, 2008; Gladwell, 2005; Levinson, 1995; Stanovich & West, 2000).

System 2 is the deeper level of thinking. It requires much more energy to perform and has the capacity to analyse, question and be more circumspect of the surroundings than System 1. System 2 has the ability to influence System 1 thinking, and the computational style of thought will often revert to basic System 1 thought when the decision maker is tired or if the particular problem is not understood properly (Kahneman, 2011; Stanovich & West, 2000).

In his book "Blink: The Power of Thinking without Thinking", Malcolm Gladwell (2005), described how people make snap judgements on things based on their intuition. The example Gladwell used is of the Greek sculpture expert, that picked up that a statue was fraudulent within a few moments of seeing it, even though she was not quite sure why. Over time and through intense analysis the statue was proven to be a fake.

Expert intuition is developed from naturalistic decision making, which is a certain type of expertise that has developed from hours of continual practice in the same repeatable circumstances (or very similar environment) (Kahneman & Klein, 2009). In this case System 2 thinking, through hours of repetition and deliberate practice has managed to influence System 1 to be able to analyse certain circumstances correctly in the blink of an eye.

The problem with relying on System 1 thinking is that in most situations people are not experts. The situation may not be a repeatable incident, or the outcome may not have been practised countless times before. This leads to heuristics being used that could potentially lead to biased decision making (Kahneman, 2011; Levinson, 1995; Stanovich & West, 2000).

2.3 Heuristics and Biases

A heuristic is an inferential rule that allows people to change difficult (or unknown) problems into simpler ones (Slovic et al., 1981). People, when using System 1 thinking, are prone to using heuristics that can lead to errors in judgement (Iqbal, 2013; Stanovich & West, 2000). Utilising different heuristics in erroneous environments may lead to further biases of various kinds. It is important to note that many, if not most, heuristics do not lead to biases an actual assist in the decision making process (Kahneman, 2011).

Some of the more common biases are confirmation biases, where individuals use information that confirms their point of view and reject information that opposes that perspective (Stanovich & West, 2000). Availability bias, the utilisation of available information over the base rates (Tversky & Kahneman, 1973). Overconfidence bias or the above average effect, where people believe that they can beat the odds due to them being involved (Williams & Gilovich, 2008). Optimism bias, where people ignore what has happened to other as they believe it won't affect them (Kahneman & Lovallo, 1993; Lovallo & Kahneman, 2003). Egocentric bias, where people think they are better than everyone else (Ross & Sicoly, 1979). Finally hindsight bias, as it worked in the past it must work in the future (Agans & Shaffer, 1994; Fischhoff, 1975).

The availability heuristic as described by Tversky and Kahneman (1973) plays an important role in the three key constructs of the dissertation as it forms the basis of underdog bias (Davidai & Gilovich, 2016). It has significant influence in how people perceive risk (Slovic et al., 1981) and on how they rate themselves (Schroeder et al., 2016).

2.3.1 Availability Heuristic

The availability heuristic describes merely the use of memories that are used in the decision making process that are more available than others. For example, a person when asked to determine the likelihood of a couple getting divorced, tend to use the available memories of their friends, family and acquaintances that have got divorced. They ignore the base rates of divorce in the general population (Tversky & Kahneman, 1973). The “clinician’s illusion” described how not only do normal people get fooled by the heuristic but even professionals are caught by the bias of their memories (Cohen & Cohen, 1984).

People will tend to ignore the base rate typically for one or two reasons. Firstly they do not know the base rate, so their own experience is the only thing they have to fall back on when answering the question. Kahneman (2011) describes this as the “what you see is all there is” effect (WYSIATI). Another way of looking at this is out of sight out of mind, where people fail to understand that just because their available information answers the question it does not take into account the information that they do not know (Slovic et al., 1981).

This type of thinking is very typical of System 1; the mind cannot conceptualise the actual question of what the likelihood of a couple getting divorced is so instead they offer an answer to the different question of what is the likelihood that someone in their friendship/family/acquaintance group will get divorced (Levinson, 1995).

The second way that the availability heuristic impacts individuals is through the sensationalism of different inputs. Slovic, Fischoff, Lichtenstein and Roe (1981) illustrate that biased newspaper coverage of sensationalised deaths from murder and accidents cause people to think that these causes are more probable than death from disease or stroke. The information that we take in shapes the decisions we make. The fear of flying (although a lot safer than road travel) is another example of sensationalism due to the availability of the knowledge of the accidents (Kahneman, 2011).

The availability heuristic has enormous power to influence the way that individuals understand the world around them, as we experience the world in our unique way. This means that what we can recall (what is available to us) shapes the way that we see the world (Ross & Sicoly, 1979; Taylor, 1991).

2.3.1.1 Underdog Bias

Underdog bias is based on the concept that individual’s feel their headwinds and barriers more than they feel their tailwinds and benefits (Davidai & Gilovich, 2016). This is more salient when those headwinds and tailwinds are compared to what others experience. The underlying theory was based on negative events (barriers or hardships) having to be overcome, whereas positive events (benefits and tailwinds) are often forgotten quickly. The paper argues that those negative events are not just more salient in memory but are also more available.

The authors argue that the events we have faced, that have a barrier effect on us, become more available when looked at in comparison to what others have gone through (Davidai & Gilovich, 2016). Effectively this means that individuals see the barriers they have faced as more salient when compared to the benefits they have received.

This creates a paradox as memories tend to have a positive bias in the long run (Rozin & Royzman, 2001; Taylor, 1991). Taylor (1991) goes further to argue that in the short run people tend to spend time and energy trying to explain away negative events because they need to be overcome, whereas positive events are expected as “normal human thought is skewed in a positive direction” (p.78). In the long run minimisation of negative events occurs as “people actively attempt to reinterpret negative events to be at least neutral or positive” (Taylor, 1991), p. 73), or as Rozin and Royzman (2001) describe it: “it is not that negative memories are inherently less memorable, but rather that they are neutralized over time” (p.305).

This paradox of underdog or barrier memories as more available may also be due to how people tend to see themselves in the world. People may see themselves as the hero in their story. They are the only person that has had to go up against and experience the events that they have had to. Thus when people feel like they have overcome something they discount what others have had to go through to get to the same place, seeing themselves as having to face unfair conditions along the way (Davidai & Gilovich, 2016).

The impression of having to overcome bigger barriers than others may lead people to believe that their contributions are more valued than others, particularly in a team environment. This sense of self-importance may be a factor that leads to self-attribution management where individuals overestimate their contribution to a team effort (Ross & Sicoly, 1979; Schroeder et al., 2016). This overestimation of an individual’s contribution of work may start to feel like reality to the individual, creating an inflated sense of self-rated performance (Davidai & Gilovich, 2016).

There is nevertheless a darker side to underdog bias where individuals feel that they have been unfairly treated. If people perceive that others are getting an easier ride or they are facing tougher boundaries than others, there have been instances (one known experiment) where individuals are happy to cut corners or bend rules to level the playing fields (Davidai & Gilovich, 2016). The experiment was done using academic faculty that specialise in experimental and non-experimental accounting. Both the experimental and non-experimental faculty participants thought that the other had it easier. Interestingly each faculty (on average) were happy to be more accepting of questionable research practises to make sure that the perceived disadvantage was corrected (Davidai & Gilovich, 2016). This is consistent with the work of Tamborksi, Brown and Chowning (2012) that showed people may engage in questionable ethical behaviours to get what they feel they deserve.

Although Davidai and Gilovich (2016) tacitly mentioned the link between self-attribution and underdog bias by describing how individuals that think that they face stiffer headwinds than others also think that they are more entitled to a larger share of benefits. They do not test if underdog bias may be a factor in the level of self-attribution, self-rated performance or overconfidence bias.

2.3.1.2 Overconfidence Bias

Overconfidence bias or an inflated view of self-rated performance is a construct of multiple different biases (availability, optimism, egocentric and hindsight to name a few) that result in people having a perspective that on average they are better than average (Guenther & Alicke, 2010; Taylor & Brown, 1988; Williams & Gilovich, 2008).

Overestimating of an individual's performance can be seen in two similar but distinctly different ways. The first is through self-attribution, where an individual judges their contribution to a team to be more substantial than what was actually contributed. In many experiments, this has resulted in the sum of each individual's claimed credit being more than 100% (Schroeder et al., 2016). The second factor in overconfidence bias is hindsight bias, which describes how historical events and outcomes are not necessarily the way to predict future outcomes (Fischhoff, 1975). Hindsight bias will be discussed in detail further into to dissertation.

The overestimation of individual contribution was originally described by Ross and Sicoly (1979) in their landmark paper on egocentric bias. The pair argued that egocentric bias or inflated self-rated performance is a function of four main factors: selective encoding, differential retrieval, informational disparities and motivational influences.

Selective encoding is based on the individuals own thoughts and ideas. The availability of an individual’s thoughts is more likely to be remembered when compared to a different member of the team’s inputs. Those thoughts and actions may fit better into the narrative of the team’s total work from the individual’s perspective than the other team member’s inputs (Ross & Sicoly, 1979; Taylor, 1991).

Availability bias could also be a problem that results in the retrieval of personal information as opposed to other member’s work when reviewing the contributions of the team. People tend to recall what they contributed to the team as it is easier to recall what their actions were rather than what someone else’s was (Ross & Sicoly, 1979; Schroeder et al., 2016; Tversky & Kahneman, 1973).

Information disparities can happen when reviewing what was done by the team as only the individual has full sight of what they needed to get done as part of the task rather than what the others have had to get through on their own. This is a case of “what you see is all there is” (WYSIATI) (Kahneman, 2011).

Egotism bias can be a factor, where an individual may overrate their contribution to the team based on the fact that it may enhance their self-esteem when they focus on their inputs to the team over other peoples. An individual may see their contribution as more valuable than what the others have done (Ross & Sicoly, 1979; Taylor, 1991).

Individuals may be worried about accurate self-assessment as it may deflate their view of themselves. In this way, people tend to be primarily concerned with protecting their own opinion of themselves. Individuals may end up self-handicapping, or described differently, come up with a barrier (lack of sleep for example) that if they succeed in their task it only goes to serve their ability, but if they fail then it was the because of the barrier (Hirt, Deppe, & Gordon, 1991)

The second factor in overconfidence bias is hindsight bias. Individuals that have had previous success may determine that their future success should be based on their previous success. Unfortunately, this is not necessarily true, particularly in complex non-repetitive environments (Agans & Shaffer, 1994; Fischhoff, 1975).

Tversky and Kahneman (1973) indirectly described hindsight cleverly with “associative bonds are strengthened by repetition is perhaps the oldest law of memory known to man. The availability heuristic exploits the inverse of this law, that is, it uses the strength of association as a basis for judgement of frequency” (p. 164). The availability of success (in the past) leads to an individual’s inflated self-rated perception in the future.

Taleb (2007) in his book the “Black Swan” agreed with hindsight bias, stating that the past is a poor predictor of the future but added his concept of the narrative fallacy where people try to connect the past events (even if they are random) as a rationale for the future. Individuals armed with 20:20 hindsight piece together seemingly random information to give as reasoning for the event, they then are armed with this information, attempt to use it to predict the future.

Hindsight bias is not limited to an individual’s perspective of their performance. A strong reputation coming into a new role or good past performance may cause a manager or leader of a team to give an individual special treatment as they expect continued strong performance in the future. In extreme cases, this can lead to a halo effect for the individual (Forgas, 2011). This inflated view of others can affect the individual as they start to see themselves as better than they are through the encouragement they get.

Another way of describing overconfidence bias or above average effect is the Lake Wobegon Effect where all the residents of the fictitious town of Lake Wobegon are above average (Hayes & Schaefer, 2009). The Lake Wobegon Effect has been cited as one of the reasons why CEO pay has increased above the average worker pay as no company wants to admit that their CEO is below average (Hayes & Schaefer, 2009). This is another example that overconfidence bias not only affects how individuals rate themselves but also there are external inputs that cause individuals to see themselves as above average.

Kahneman and Lovallo (1993; 2003) describe optimism bias as a function of hindsight bias where, executives, in particular, use the previous success of projects to determine the outcome of future projects. Teams tend to use their internal perspective (what they believe their team can do) as the basis for the success of projects rather than looking at the available information in the market causing optimism bias in individuals.

Optimism bias is then joined by competitor neglect (a cognitive bias where people make decisions without taking into account competitor activities) to create the planning fallacy. This mix of optimism as well as refusing to take into account what is happening in the market can create a toxic mix where executives take risks that typically result in gross underestimation of the time and costs needed to complete a project, forcing the best possible scenario to become the standard that needs to be delivered against. Predictably this, generally, results in project delays and over expenditure (Lovallo & Kahneman, 2003).

The combination of availability bias, egocentric bias, hindsight bias, and optimism bias all contribute to overconfidence bias or the better than average effect (Williams & Gilovich, 2008). It has been tested where the BTAE effect when added to other cognitive biases can cause CEO's to take risks that outweigh the benefits (Lovallo & Kahneman, 2003). It is also a factor in the perception of risks as individuals believe that they can judge risk with a high degree of certainty (even though it is unlikely) (Slovic et al., 1981).

2.3.1.3 Risk Perception

In their seminal paper Slovic, Fischhoff, Lichtenstein and Roe (1981) described how no matter how much care someone takes in determining the level of risk there will always be a large amount of subjectivity in the assessment. This is because risk determination requires some foresight or a prediction from an individual. The difficulty with anything that needs to be predicted is that it is open to a level of bias from individual experience, available information and particular perception. The paper goes on to break risk perception into two main causes of bias, availability and overconfidence.

Availability bias has been shown to affect risk perception as individuals recall their own experiences to assess the different levels of risk. This can be seen in the use of situations that individuals went through as a predictor of the future which may not necessarily, e.g. both parents died in a car accident which inflates the perceived risk of driving (Kahneman, 2011).

The availability of information can also cause individuals to perceive a lower risk than reality. In the same way that a car accident may be the reason to overstate the perceived risk of driving, if an individual has never had an accident, they may perceive the need for a safety belt as superfluous as they have never had an accident previously (Slovic et al., 1981).

The lack of information can cause an out of sight out of mind problem where people can neglect real risks purely based on the fact that they don't know about it. This lack of available data is an example of "what you see is all there is" (WYSIATI) phenomenon and System 1 thinking (Stanovich & West, 2000).

News coverage that sensationalises certain information can also cause people to misinterpret the actual risk and either inflate or deflate the risk that is perceived by an individual. In extreme cases, this can cause people to develop phobias to low risk (or relatively low risk) activities such as flying in commercial aircraft (Slovic et al., 1981).

Overconfidence appears to have just as a large an influence on the subjectivity of risk perception as availability bias. People tend to think that they understand risk with a high level of confidence. This belief in their convictions allows them to think they have mitigated the risk, lowering their risk perception (Heath & Tversky, 1991; Hoffmann, Post, & Pennings, 2013).

Experts tend to be just as likely to be overconfident in their perception of risk which can create problems that can play out as the planning fallacy, where the absolute best case scenario becomes the expected or estimated scenario (Lovallo & Kahneman, 2003).

The planning fallacy, however, does require that the individual that perceives the risk takes the action that they believe will mitigate the risk. In essence, they take on the risk they perceive, moving the perceived risk into the individual's propensity for risk. Gilovich and Douglas (1986) explained that individuals that have the appearance of control over an outcome have a higher propensity for risk than if there is no control (or the outcome is truly random). By actually taking the risk, the individual moves from risk perception to risk propensity.

2.4 Loss Aversion, Prospect Theory and Risk Propensity

Just as utility theory has dominated economic theory in determining how a rational agent may act, it has also been the historical base for analysing an individual's decision when faced with risk. The von Neumann-Morgenstern expected utility function provides a simple mathematical framework that predicts an individual's expected values in the same way, regardless of the risk attached to it. The expected utility function only uses the mathematical understanding of risk (or probability) to determine preferences. It does not take into account how an individual's preferences may change depending on the situation. For example, a rational being would value a 50% chance of winning R1 000 equal to a 100% chance of winning R500 as each choice has an expected value of R500 (Baye & Prince, 2013; Iqbal, 2013).

Kahneman and Tversky (1979) argued that utility theory did not account for what an individual would choose to do. They offered an alternative perspective in prospect theory, which simply stated that individuals were risk averse when faced with a potential gain and where risk seeking when faced with a potential loss.

This means that individuals choose a sure bet over a potential return when faced with a gain. For example, when faced with a 50% chance to win R1 000 or R450 for sure, individuals tend to choose the R450 (Kahneman & Tversky, 1979). But in expected utility theory the rational choice would have been the 50% chance of R1 000 as it has an expected value of R500 (and R500>R450). This means that individuals are not rational, or as Kahneman and Tversky (1979) point out, expected utility theory does not adequately cater for risk preferences in individuals, which is where prospect theory comes in. It attempts to explain the choices people make under uncertainty in a more reality-based scenario.

Prospect theory goes on to describe that when faced with a loss, individuals tend to be risk seeking. As an example when someone is faced with a sure loss of R450 or a 50% chance of a loss of R1 000 they tend to choose the 50% chance of losing R1000. This is the opposite of what could be expected in the gain scenario. Therefore, individuals are risk averse when faced with a gain, but are risk seeking when faced with a potential loss (Kahneman & Tversky, 1979).

This paradox of risk seeking when faced with losses and risk aversion when facing gains allowed Kahneman and Tversky (1979) to conclude that people were naturally loss averse or critically “losses loom larger than gains” (Kahneman, 2011, p. 284) when faced with the option of a potential loss or a potential gain (i.e. a 50% chance of losing R500 or a 50% chance of losing R750). Novemsky and Kahneman (2005) did a follow up to prospect theory and found that individuals, in general, had a ratio of between 1.5 and 2.5 for the gain against the loss.

That variation of the ratio showed that individuals have a different level of risk propensity depending on their preferences. Prospect theory and expected utility theory attempt to explain this difference away by arguing that reference points make a difference to an individual. The reference point or starting point is the value the individual starts with before the decision needs to be taken on risk. For example, if an individual stood to gain R1 000 from their base of wealth of R500, they are likely to be more risk averse than an individual that stood to gain R1 000 from a base of R10 million (Baye & Prince, 2013; Kahneman & Tversky, 1979).

While reference points explain away some of the difference in the variance of the loss aversion ratio, there is another perspective that may explain some of the variation. Thaler (1980) developed the endowment effect which states that people value certain items they possess at more than they are willing to pay for the same item. Simply, this means that an item has more value to an individual once they possess it than when they had to purchase it. The endowment effect did not become popular until Thaler collaborated with Kahneman and Knetsch (1990) to stress test the theory.

The trio managed to repeatedly show that an item (typically one that is not traded regularly) has more value to the seller than it does to the payer. This creates a disparity in economic theory where the value of an item where an individual is not willing to purchase the same item for that value but nor would the same individual sell the item, creating a dead zone of trade (Kahneman et al., 1990).

Even with reference points, and endowment effect explaining why there is a disparity in the ratio of loss aversion an individual is willing to take on, it does not account for the full value of why different people choose riskier (or safer) options than others. Some individuals will tend to take more risks than others; this can be seen in entrepreneurs that have a blind belief in their firm's ability to succeed (although this is influenced by biases (Kahneman, 2011) and through outside pressures (Lovallo & Kahneman, 2003)).

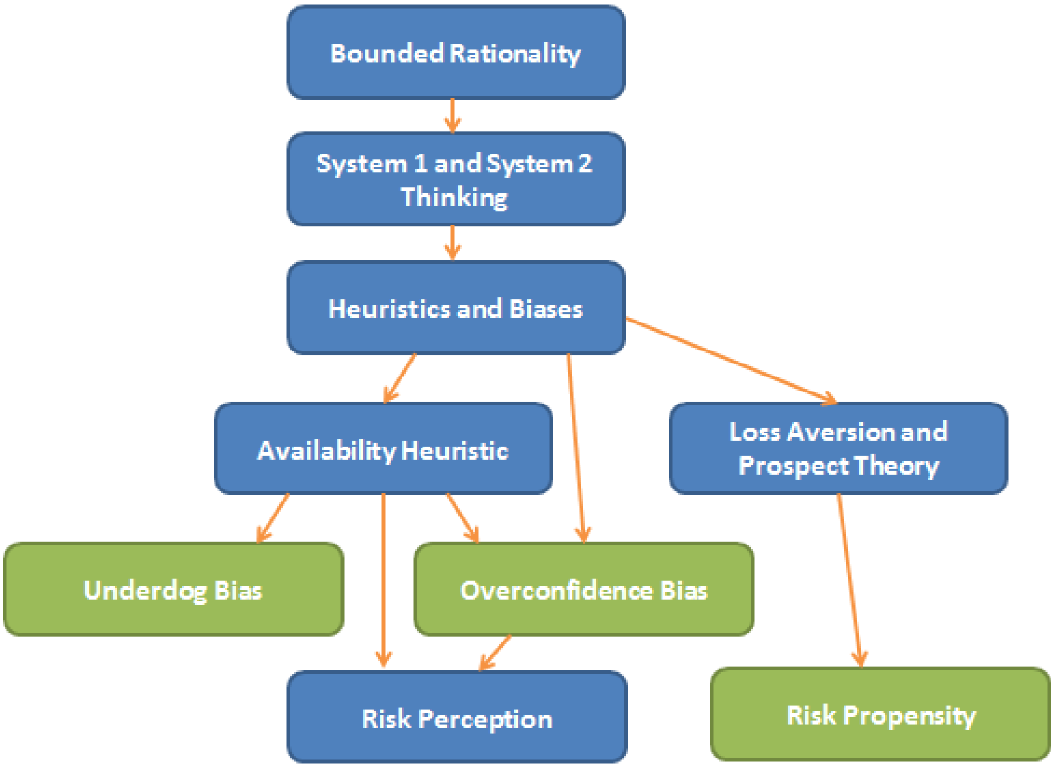
Individuals tend to also have a changing risk propensity depending on the feeling they get from a particular option. King and Slovic (2014) showed that there was evidence for feelings as a basis for risk assessment individuals and showed further that particularly in IPOs (initial public offerings) professional investors were swayed by the affect heuristic or their feeling towards the IPO.

An individual's natural level of risk propensity will influence the way that they behave (Iqbal, 2013), but there are certain outside influences that will either make the individual more risk seeking or more risk averse (Lovallo & Kahneman, 2003). This paper will try to understand if there is a directional correlation between underdog bias and self-rated perception in the risk propensity of individuals.

2.5 Conceptual Framework

The existing literature gives an insightful foundation on the three constructs (underdog bias, self-rated performance and personal risk propensity). The following framework gives an outline of the theoretical grounding as well as an explanation of what is currently known followed by what the paper seeks to clarify in what is unknown to derive the hypotheses.

Figure 1: Theoretical Grounding of the Constructs



2.5.1 What Is Known

Underdog bias, self-rated performance and risk propensity are unique constructs, but all derive from the same psychological theory. People and their experiences influence the way that they interpret their current standing and future decisions. Individuals use two different types of thinking when understanding the world around them and the future they face. (Stanovich & West, 2000)

Using the different systems of thinking people can use shortcuts, or heuristics to answer questions or problems that they face, be it about the world around them or in rationalising their experiences. These heuristics and biases can influence individual's perspectives that result in perspectives that are skewed from real life but are nonetheless real to those individuals (Kahneman, 2011).

The underdog bias comes from availability heuristic where individuals believe that they have had a tougher time getting to where they are than their peers. Simply this is due to the availability of negative personal experiences against the barriers that others have faced. In extreme cases this may lead to questionable behaviour where people attempt to level the playing field (Davidai & Gilovich, 2016).

Self-rated performance has various factors (optimism, availability, egocentric and hindsight biases) that can cause individuals to perceive their capabilities to be greater than the average (Guenther & Alicke, 2010; Williams & Gilovich, 2008).

This better than average effect or overconfidence in your abilities can, if combined with other cognitive biases, lead to individuals putting themselves into tougher positions where they need to deliver on decisions that are unlikely to happen or only happen in the absolute best scenario (Kahneman & Lovallo, 1993).

Biases and heuristics also influence the perception of risk. Slovic, Fischhoff, Lichtenstein and Roe (1981) describe that individuals are influenced by overconfidence and availability when they perceive the level of risk of any decision.

The perception of risk, although closely related to risk propensity, does not indicate what level of risk individuals are willing to take on in their decisions. Individual risk propensity is driven by risk aversion when faced with gains and risk seeking behaviour to attempt to prevent losses (Kahneman & Tversky, 1979).

2.5.2 What Is Unknown

The three constructs come from behavioural economics, and all three are influenced by different biases and heuristics (Davidai & Gilovich, 2016; Hirt et al., 1991; Kahneman & Tversky, 1979; Kahneman, 2011). Each construct has been tested individually, but none of the constructs had been tested to determine if they are related.

Davidai and Gilovich (2016) tacitly mentioned the link between self-attribution and underdog bias. “The belief that they have faced stiffer headwinds than others can also make people feel entitled to greater benefits than they’ve received” (p. 837), they do not test if underdog bias may be a factor in the level of self-attribution or self-rated performance.

Self-rated performance has been previously linked to risk perception by observation in Lovallo and Kahneman’s (2003) paper on the planning fallacy and CEO strategic decisions. But to the best of the author’s knowledge, there has been no specific testing of self-rated performance and risk propensity.

Underdog bias has been shown to cause people to cut corners and take short cuts (Davidai & Gilovich, 2016). This type of behaviour can be linked to risk propensity as the individuals cutting corners are taking a risk with their reputation and the potential disciplinary action if caught. But underdog bias has not been tested to determine if there is a correlation between underdog bias and personal risk propensity.

Individual risk propensity has been studied in detail and it has been proven difficult to determine if people are risk seeking or risk adverse (Iqbal, 2013). Lovallo and Kahneman (2003) showed that there are outside factors that can influence an individual's risk perception. To the best of the author's knowledge, there have been no studies to indicate if underdog bias and self-rated performance are tested to see if they are relational or correlational to personal risk propensity.

2.6 Conclusion

People have an individualised experience of the world around them. Those different experiences and in some cases lack of experiences have been shown to shape the way that those people see the world. They develop different mental models that have the potential to influence their different systems of thinking (Stanovich & West, 2000).

Those different mental models or shortcuts are called heuristics that allow our brains to use an instinctual method of thinking (System 1) in the way that we judge the world. The problem is that under certain circumstances those heuristics can cause us to view the world in a way that is different to reality (Kahneman, 2011).

The three constructs reviewed in the paper describe how different experiences can create different views of themselves. Underdog bias explains how people see themselves based on things that they have had to overcome (Davidai & Gilovich, 2016).

Self-rated performance is a construct of different biases that depict how individuals tend to think of themselves as better than average (Guenther & Alicke, 2010) and they tend to overvalue their performance in teams (Schroeder et al., 2016). Overconfidence or an inflated view of self-rated performance is also a major factor (along with availability bias) in determining how individuals and their unique experiences shape their risk perception. This perception of risk carries with it a large amount of subjectivity that allows the individual to be particularly susceptible to bias and System 1 thinking (Slovic et al., 1981).

The final construct of personal risk propensity is developed inside the concept of prospect theory and how individuals are risk averse. There are certain cases where individuals find themselves as seeking risk but this is typically when faced with a loss or when the reference point makes the potential reward minuscule in comparison to the risk (Kahneman & Tversky, 1979). These constructs have been studied previously but have not been studied in relation to one other.

3 Hypotheses

3.1 Introduction

The three different constructs all come from the same theoretical base of bounded rationality and even further from heuristics and biases (Kahneman, 2011). All three have very clear grounding and have been studied in depth by different researchers, but it does not appear that any of the three constructs have been studied together.

This paper takes a view on the three different constructs in relation to one another, to determine if there is a positive correlation between the three sets of pairs (underdog bias and self-rated performance, underdog bias and personal risk propensity, and finally self-rated performance and personal risk propensity).

3.2 Hypothesis One: There is a positive correlation between underdog bias and self-rated performance

Davidai and Gilovich (2016) almost as a footnote mention a self-attribution as a possible outcome of underdog bias. Self-attribution is a factor of self-rated performance through egotism bias (Ross & Sicoly, 1979).

This indicates that there may be a possibility that the higher the level of underdog bias the higher level of self-rated perception in an individual. This study will try to understand if there is a relationship between underdog bias and self-rated perception and if that relationship is positively correlated.

H_0: There is no statistically significant positive correlation between underdog bias and self-rated performance.

H_1: There is a statistically significant positive correlation between underdog bias and self-rated performance.

3.3 Hypothesis Two: There is a positive correlation between underdog bias and personal risk propensity

The final experiment in Davidai and Gilovich's (2016) paper on underdog bias showed that when individuals feel like they have been unfairly treated, they can take to certain dubious means to try and right the wrongs they perceive. By righting these perceived wrongs, the individuals take on the added risk that if they are caught there will likely be recourse to their actions. The change in their actions caused by the underdog bias could be perceived as an increase in risk propensity.

The paper will understand if that the theorised increase in risk propensity is correlated to an increased level of underdog bias.

H_0: There is no statistically significant positive correlation between underdog bias and personal risk propensity.

H_1: There is a statistically significant positive correlation between underdog bias and personal risk propensity.

3.4 Hypothesis Three: There is a positive correlation between self-rated performance and personal risk propensity.

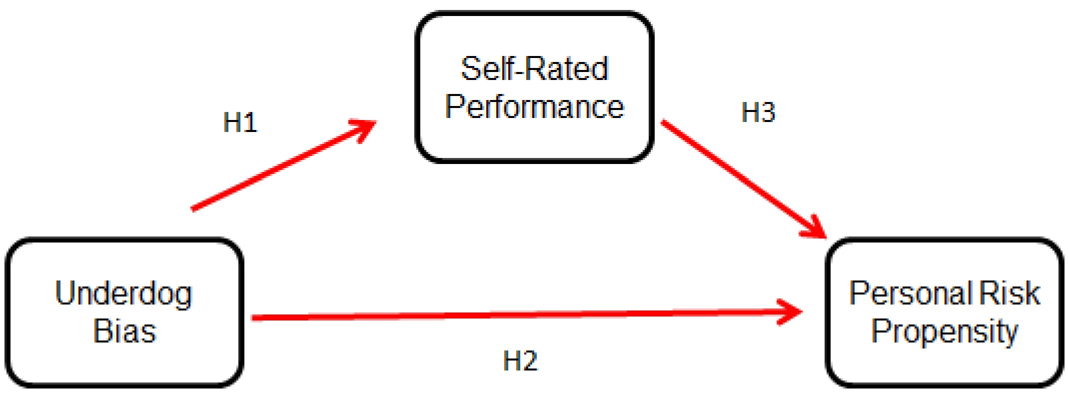
Self-rated performance through overconfidence has shown that it influences risk perception (Lovallo & Kahneman, 2003). Although risk perception and risk propensity are different constructs, it is possible that both may be influenced by self-rated performance in the same way.

The study will understand if there is a relationship between self-rated performance and personal risk propensity and if that relationship proves to have a positive correlation among the constructs.

H_0: There is no statistically significant positive correlation between self-rated performance and personal risk propensity.

H_1: There is a statistically significant positive correlation between self-rated performance and personal risk propensity.

Figure 2: Hypothesis Tree



4 Research Methodology

4.1 Philosophy

The research philosophy of the paper is one of positivism. The nature of the paper is to understand and measure the relationship of variables that represent people's personal perspective of their underdog bias, how they rate themselves and the riskiness of their behaviour. This allows the study to examine if there is evidence of a correlation between the different variables (Oliver, 2004).

4.2 Design

The existing literature provides an extensive base from which hypotheses have been derived. This makes the study deductive in its approach as the theory has guided the research which we want to test and confirm (Bryman & Bell, 2004).

The study is explanatory in nature as it is "research that focuses on studying a situation or a problem in order to explain the relationship between variables" (Saunders & Lewis, 2012, p.113). The investigation looked to uncover a relationship between the measured variables and investigate what (if any) relationship exists between them.

To get the required information the study used a survey questionnaire design, this is because the survey is the most often used and most reliable method of collecting data that is not directly observed (Swanson & Holton, 2005), which aligns with attempting to explain the relationship between the variables.

A survey design has other positive benefits. It ensures that the feedback from respondents is standardised and can be easily quantified. "The data collected using a survey strategy can be used to suggest possible reasons for particular relationships between variables and to produce models of these relationships" (Saunders, Lewis, & Thornhill, 2009). This allowed the study to be mono method that is exclusively quantitative.

There are drawbacks to the survey design and quantitative methodology. The main problem is the limited detail that can be extracted from the predesigned questions (Zikmond, 2003). The researcher does have the ability to adapt the questionnaire during the interview in the same way as a qualitative interviewer has.

The survey was administered to each prospective respondent only once. This makes the research cross-sectional in nature as it measures the perspective of the participant at that specific point in time (Saunders et al., 2009). Due to the time frames of the study and to be pragmatic this study can only be cross-sectional. By being cross-sectional, the data collected from the research ignores the respondent's ability to change their perspectives of themselves in time.

4.3 Population

The study was targeted at individuals involved in the investment community. The investment community was chosen for two main reasons. Firstly the investment community regularly has to make decisions where the level of risk of an investment is weighed up against the potential return. If the investment committee has a slightly elevated risk appetite, then the actual risk level of a particular investment may be negated due to the underdog bias and self-rate perception of the team.

The second is that the risk level that investment committee takes on is part of the product that is sold to their customers. Private investors that provide the capital for the investment community (e.g. pension funds, private individuals) are sold a level of risk when they invest their capital with the investment funds. If the individuals that make the decision have a higher appetite for risk due to their underdog bias and self-rated performance levels, then the product being sold to the capital providers is incorrectly represented (unconsciously or not).

The individuals are either responsible for or part of the decision team that decides on whether or not an organisation is going to invest in a business or instrument. Broadly this group can be described as any one part of the investment team of private equity firms, insurance companies, investment banks, private wealth houses, stock brokerage firms, assets management companies, hedge funds, or other investment houses. The population will be based in the South African investment community to encourage continuity in the macroeconomic factors that the teams face.

The study has chosen not to broaden the population to those individuals that have input into the valuation of potential assets but are not part of the decision team. This is because the level of risk that these individuals are willing to take on is not relevant to the firm, as they are not part of the decision system. As individuals that do not consistently engage in the investments, they are prone to the endowment effect where they believe the asset they bought is worth more just because they own it (Kahneman et al., 1990). By including these individuals in the survey, it would reduce the validity of the study.

Although if the study shows a relationship between underdog bias, self-rated performance and personal risk propensity then surveying the potential members of the decision making team before they are appointed may prove to be useful.

The researcher acknowledges that other individuals are involved in the investment decisions of various organisations (members of a firm's mergers and acquisition team, board and leadership teams that approve the high-level acquisitions). These individuals, although part of the investment community in a very broad sense, do not tend to deal specifically with identifying returns for external investors through funds. As they deal with external funding as a vehicle for investment. This changes the need for a risk mitigation policy. The returns in a traditional investment business are the mechanism for the measurement of success. Whereas teams that deal in the occasional investment focus their attention on other measures (e.g. revenue generation, profitability, group synergies, etc.).

By excluding these non-traditional investment decision makers and focussing exclusively on respondents that form part of the decision making teams the data collected for the study will be more homogenous and carry less variation.

4.4 Unit of Analysis

The unit of analysis for the study is the individual respondents of the survey (i.e. the members of the investment decision making team in the different investment houses). These are the individuals that have populated the survey questionnaires from which the data was collected from.

4.5 Sampling Method and Size

A sampling frame could not be developed from the target population. This is because the list of investment houses in South Africa is large and mainly not indexed. When this is multiplied by the number of people involved in decisions making teams (many organisations have multiple investment teams) the likelihood of getting the entire sample frame was unlikely. Due to this constraint, the research has used non-probability sampling.

The study has primarily used purposive sampling to ensure that the respondents are in line with the target population. Seven hundred and ninety four individuals were selected to be part of the purposive sample. An introductory email was sent to each of the purposive sample and of those 184 respondents indicated they would participate in the survey. They did this by sending a response email.

This equates to a 23.2% response rate, which is in line with the findings of Deutskens, Ruyter, Wetzels and Oosterveld (2004) who found that the response rate of 20.4% was typical in a cold calling email of investors. The researcher chose not to send follow up e-mails to the potential respondents as a follow up email has been shown to have an insignificant difference on the response rate (Deutskens et al., 2004).

In addition to the purposive sampling, snowball sampling has been used as a secondary technique to ensure the sample is increased. This was done by asking the respondents of the purposive sample who agreed to participate to identify other potential respondents for the survey.

Saunders and Lewis (2012) comment that "respondents selected for a snowball sample are most likely to identify others who are similar to themselves, resulting in a homogenous sample" (p.140), although this is a positive reflection on snowball sampling the researcher does lose oversight in who responds to the questionnaire, losing the guarantee that all respondents are from the target population.

It is unknown as to how many individuals were asked to be part of the snowball sample (as some emails the researcher may not have been copied in on) there were an additional eight responses to the survey outside of the 184 that were part of the purposive sample. This is an increase of 4% on the total numbers of surveys, an appreciated increase but not a larger significant increase.

Non-probability sampling (purposive and snowball) does increase the risk of sample error but this can be combated by increasing your sample size. In practice, sample size can be estimated by using the following function (Wegner, 2016):

$$n = z^2 \frac{p(1-p)}{e^2}$$

Under a 5% confidence interval, a population proportion rule of thumb of 0.5 ("using p = 0.5 is the conservative strategy to follow" (Weiers, 2008, p.295)), and an acceptable margin of error of 10% the minimum number of respondents needed for the survey is 97, or simply rounded to 100.

As the survey received 192 responses, it was well above the target of 100 responses. Unfortunately, the 192 responses were not all usable as some participants chose to leave the survey before answering all or most of the questions. This resulted in the final number of usable surveys of 161 or described differently 16.1% of the surveys had to be discarded as incomplete or as extreme outliers.

The 161 usable surveys put through the same sample size estimation function represent an allowable error of 7.7% (holding all other factors constant) which was a slight improvement on the 10% target (Wegner, 2016; Weiers, 2008). The demographics of the sample of the

161 respondents will be presented in the next chapter.

4.6 Measurement Instrument

A survey in the form of a questionnaire has been used to collect the data from the respondents. The questionnaire was administered electronically. The benefit of doing the questionnaire electronically was the ability of the respondents that are purposively sampled to forward on the link to other potential respondents (snowball sampling).

The questionnaire has five parts to it. The first part is a preamble that includes a basic introduction to the research, the online consent form and some introductory questions pertaining to the demographics of the survey respondents. This allowed the respondents that do not satisfy the correct criteria to be excluded from the data, protecting the research from some of the risks of snowball sampling. Although due to the purposive sampling and the limited number of snowball respondents no one was excluded from the study because of unsuitability.

Table 1: Questionnaire Summary

	Information Tested	Number of Questions
Section 1	Consent form and Demographic Data	7
Section 2	Underdog Bias	8
Section 3	Self-Rated Performance	12
Section 4	Risk Propensity – RPMS	10
Section 5	Risk Propensity – Prospect Theory	10

The demographic data also allowed the paper to ascertain if different demographics, such as age or level of education, depict a higher or lower (on average) score on each variable. For example people with less education may be prone to a higher level of underdog bias, or are individuals with more years of experience less likely to have a risk propensity than others with less experience. Using descriptive data analysis the different demographics were able to be tested to see if there are significant differences in each of the three constructs.

The other four parts of the questionnaire were specifically designed to measure each of the individual constructs. Section two tested underdog bias, section three tested self-rated performance, section four tested personal risk propensity using a new scale developed specifically for the research, and section five tested personal risk propensity using prospect theory. The order and grouping of the questions in each section was tested through the pilot studies to prevent respondents from being influenced in anyway (Saunders & Lewis, 2012). The questionnaire is part of Appendix 1.

4.6.1 Underdog Bias Construct

The underdog bias construct was designed to measure an individual's perspective based on what they have gone through in the past compared to others (Davidai & Gilovich, 2016). This makes it by design a self-reported measure as the individual needs to experience and project those comparisons. The measuring instrument was a 7 point Likert scale, the same measurement tool that was used by Davidai & Gilovich (2016), the scale is shown below in Table 2.

Table 2: 7 Point Likert Scale

6	Entirely Agree
5	Mostly Agree
4	Somewhat Agree
3	Neither Agree or Disagree
2	Somewhat Disagree
1	Mostly Disagree
0	Entirely Disagree

The questions for section two were developed using Davidai and Gilovich (2016) as well as other inputs on availability bias as outlined in the literature review. The questions were designed to understand the degree in which individuals perceive they have stiffer barriers to face than others. Table 3 indicates the questions for section two of the questionnaire.

Table 3: Underdog Bias Questions

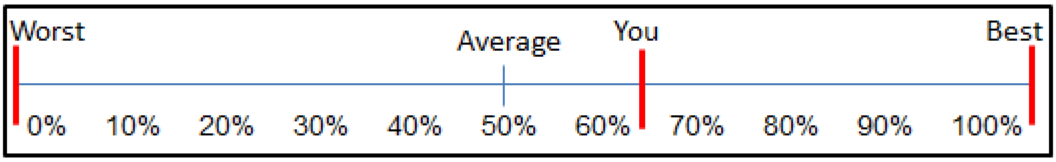
Question Number	**Question**
2.1	When I source research, I have to work harder than others to achieve the same result.
2.2	I don't know why but I seem to have more difficulty than others securing meetings with key directors.
2.3	I find it easier to communicate with investors than others. *(reversed)*
2.4	My investors are more demanding than other investors, even when I produce the same results.
2.5	My investment committee is convinced more easily to invest in my proposals than others. *(reversed)*
2.6	I have to work harder than others to get the recognition I deserve.
2.7	My investors tend to blame me more harshly than others when the market takes a downturn.
2.8	My peers get more recognition than they deserve compared to the work that they have done.

To account for the reversed questions or 2.3 and 2.5 the Likert scoring system (0-6) was reversed, i.e an answer of Mostly Disagree is scored as 5 instead of 1. The construct was then tested for validity (Pearson's correlation coefficient) and reliability (coefficient alpha or Cronbach's alpha). The remaining questions have been formed into a single combined construct variable. This is done by using each of the remaining questions score on the 7 point Likert scale and then using a simple average to give a single composite score.

4.6.2 Self-Rated Performance Construct

The self-rated performance construct was developed using a comparison variable that has been adapted from Williams and Gilovich's (2008) paper that tested the above average effect. The tool was developed for individuals to compare themselves to the average of their peers. The rating tool can be seen below in Figure 3.

Figure 3: Self-Rated Performance Scale

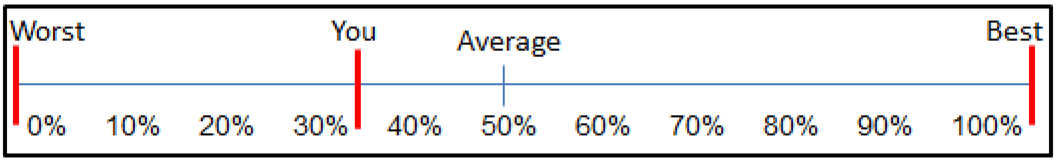


The rating scale was used to ask the survey participants to rate themselves against the average investment professional that was at 50%, for example if the professional rated themselves above average they will have a score above 50%, if they rated themselves below average their score was below 50%.

An example of how a question is as follows: Please rate yourself on the following compared to the average person (with the average being the 50% percentile) at your gym:

I push myself when I exercise:

Answer *Top:* *32%* *or below average*



The comparison scale was then combined with an adapted version of the Core Self-Evaluation Scale (CSES) (Judge, Erez, Bono, & Thoresen, 2003) to reflect the investment community and their attributes more accurately. Table 4 indicates a list of the questions.

Table 4: Self-Rated Performance Questions

Question Number	Question
3.1	I am confident I get the success I deserve at work
3.2	Sometimes I get depressed with the investment industry *(reversed)*
3.3	I generally generate returns above my targets
3.4	Sometimes when I fail, I feel like I can't choose the right investments *(reversed)*
3.5	I complete my tasks successfully
3.6	Sometimes I do not feel in control of my portfolios *(reversed)*
3.7	Overall I am satisfied with my performance
3.8	I am filled with doubts about my competence *(reversed)*
3.9	I determine what will happen in the investments we make
3.10	I do not feel in control of my success in my career *(reversed)*
3.11	I am coping with most of the problems at work
3.12	There are times when things look pretty bleak and hopeless in the investment industry *(reversed)*

To determine a score for each question the non-reversed or positive questions were adjusted to show a score of -50 as the lowest (0 in the questionnaire is -50) and +50 as the highest (100 in the questionnaire). In the reversed questions (3.2, 3.4, 3.6, 3.8, 3.10 and 3.12) the scores were calculated on the same scale except they were reversed (i.e a negative score of -25 is reversed to +25). This means that any score above zero shows that the respondent feels they are above average, and any score below zero reflects a personal opinion below average.

The construct was then tested for validity using Pearson's correlation coefficient and for reliability using Cronbach's alpha. The remaining questions were then developed into a single construct score using a simple average method.

4.6.3 Personal Risk Propensity

The risk propensity construct consisted of two parts. The first was a descriptive view of risk propensity that has been specifically designed from existing literature for the measurement of personal risk propensity in the investment community. The scale consists of ten questions that are designed to measure risk propensity, particularly in an investment environment. The scale measures investment risk propensity using a 7 point Likert scale that is similar to the underdog bias construct. The risk propensity Likert Scale can be seen below in Table 5. The ten questions that were designed to give a descriptive measure of risk propensity, or the risk propensity measurement scale, are set out in Table 6.

Table 5: 7 Point Likert Scale for RPMS

0	Entirely Agree
1	Mostly Agree
2	Somewhat Agree
3	Neither Agree or Disagree
4	Somewhat Disagree
5	Mostly Disagree
6	Entirely Disagree

Table 6: Risk Propensity Measurement Scale Questions

Question Number	**Question**
4.1	I take more risk than my fellow investors
4.2	I have worried about investment decisions I've taken knowing they are overly risky
4.3	My investment decisions are rational and are very unlikely to harm the fund *(reversed)*
4.4	I get a thrill by taking decisions that I don't know the outcome of
4.5	I have been scolded for taking risky decisions *(reversed)*
4.6	If I could take a little bit more risk I could secure a higher return for my fund
4.7	The more risk I take the better I perform
4.8	Before I make any investment I do more of a thorough analysis than others *(reversed)*
4.9	I like to take risks
4.10	I tend to take large but reasonable risk in my investment decisions

To score the reversed questions (4.3, 4.5 and 4.8) the Likert scale has been reversed, i.e. a respondent that answers Somewhat Agree will be scored as a 4 instead of a 2. The construct was then tested for validity using Pearson's correlation coefficient, followed by a test for reliability using Cronbach's alpha. Questions were removed from the construct until the validity and reliability scores were adequate. The remaining questions were then simply averaged to give a single construct score for each respondent.

The second part of the risk propensity construct was adapted from prospect theory (Kahneman & Tversky, 1979). The questions were designed to measure at what point individuals will take on risk or become risk averse. The questions are binary (either A or B) and therefore need to be measured as a total construct to understand at what point the individual chooses to accept the risk, or chooses a less optimum outcome in favour of reduced risk.

The prospect theory scale consisted of 10 questions that can be seen in Table 7 below:

Table 7: Prospect Theory Choices

Question Number	Option A	Option B
5.1	80% chance of R4 million and a 20% chance of nothing	100% chance of R3 million
5.2	20% chance of R4 million and an 80% chance of nothing	25% chance of R3 million and a 75% chance of nothing
5.3	45% chance of R6 million and a 55% chance of nothing	90% chance of R3 million and a 10% chance of nothing
5.4	80% chance of losing R4 million and a 20% chance of nothing	100% chance of losing R3 million
5.5	20% chance of losing R4 million and an 80% chance of losing nothing	25% chance of losing R3 million and a 75% chance of losing nothing
5.6	45% chance of losing R6 million and a 55% chance of losing nothing	90% chance of losing R3 million and a 10% chance of losing nothing
5.7	50% chance of losing R2 million and a 50% chance of gaining R4 million	60% chance of losing R3 million and a 40% chance of gaining R6 million
5.8	30% chance of losing R3 million and a 70% chance of gaining R2 million	50% chance of losing R3 million and a 50% chance of gaining R5 million
5.9	80% chance of losing R1 million and a 20% chance of gaining R5 million	30% chance of losing R2 million and a 70% chance of gaining R1 million
5.10	30% chance of gaining R2 million and a 70% chance of losing R1 million	20% chance of gaining R4 million and an 80% chance of losing R1.5 million

Each variable was turned transformed into its certainty equivalent score using the cumulative prospect theory formula (Tversky & Kahneman, 1992). The highest certainty equivalent score was then given a value of 0 (the least risky option) and the other score, which had a lower certainty equivalent (and generally the highest expected value) was given a score of 1 (as the riskiest option). A single score was then developed for the construct using a simple average of all ten questions to create a single prospect theory scale score for each respondent.

4.6.4 Questionnaire Piloting

After the questionnaire was developed, it was piloted. The survey was sent out to six investment professionals and two non-investment professionals to check for usability. By piloting the survey the researcher was able to refine the questions and the way that they are asked. There were minor changes to the survey (two spelling errors) but no major adjustments. There were no major errors found after distribution of the survey (that the researcher is aware of) that have caused a problem in the data collection that needs to be addressed in the findings (Zikmond, 2003).

4.7 Data Gathering Process

As the questionnaire was sent out electronically, the survey was self-administered. This allowed respondents to do the survey from the safety of their offices or homes without having anyone asking questions to them. This provides three very clear benefits over a face to face interview.

Firstly, people are prone to enhancing themselves, “the basic human tendency to present oneself in the best possible light can significantly distort the information gained from self-reports” (Fisher, 1993, p.303).

Secondly, the questionnaire was distributed by e-mail which reduces the time needed to administer the questionnaire. The survey can then be completed by anyone at any time (until the cut off) without the need to set up a meeting with the researcher.

The final benefit of the questionnaire being administered electronically was that the data was collated by the platform provider, removing the need for the researcher to input the data manually, eradicating input errors.

The data for the study was collected by emailing specifically chosen members of the investment industry. They had to conform to the population, and they had to have a readily (public) email address. The researcher then sent out 794 emails that asked if the respondent would like to be part of the survey. There were 184 positive responses from that indicated they would be happy to participate. The 184 then were emailed a link to the survey with a note asking to forward on the link to people they thought may be willing to be part of the study that fit the defined population. Resulting in 192 surveys attempted (at least one question answered). Of the 192 surveys attempted not all were usable due to unanswered questions or outlier answers. This resulted in a smaller sample size which will be discussed further in the next chapter.

4.8 Analysis Approach

The data that was collected from the online platform was sent to the researcher in MS Excel format. The data came in an unformatted form which allowed the researcher to follow a structured approach in analysing the data (adapted from Wegner (2016)).

Firstly, the data was reviewed for validity. This took into account simple searches for the 30 incomplete surveys that were left out of the useable data. Other outlier data was reviewed for validity (e.g. obviously not reading the questions) or answering the same answer every time. There was one survey that was discarded on this basis.

Once the data was scrubbed for obvious errors Pearson's correlation coefficient and Cronbach's Alpha was used to test the constructs for validity and internal consistency. Pearson's bivariate correlations should indicate that all items in the construct have a significant correlation which is seen by confidence level above 95% ($p<0.05$). Cronbach's alpha has a slightly different scale to measure internal consistency with an acceptable value that is a little more controversial. For this study, we will adopt the same outline that was used by Tavakol and Dennick (2011) of an alpha between 0.7 and 0.9 ($0.7<\alpha<0.9$).

Secondly, basic descriptive statistics or data analysis was performed to understand basic trends and simple relationships between variables. Some testing (depending on the data of each construct) was done to understand if the different demographics had significantly different results. For example, a single factor ANOVA was performed on every demographic of each construct to understand if there was a significant difference in the construct scores.

Finally, statistical modelling was performed to confirm or refute the correlations of the variables. This was done using regression modelling that was able to quantify the relationship of the constructs, critically it also measured the strength of the predictive relationship between the three constructs. This allowed the researcher to understand the predictive value that underdog bias has on self-rated performance, and the predictive value of both self-rated performance and underdog bias on personal risk propensity (Wegner, 2016).

4.9 Limitations of the Research Methodology

As in all studies, there are factors that each study may not be able to mitigate for. In relation to this study, there are many factors that may cause the results to be skewed in one direction or another. Some of the limitations are outlined below:

There will be no sample frame derived for the target population. This means that non-probability sampling will be used (purposive and snowball). Anytime non-probability sampling is used there is a risk that the sample respondents do not represent the population correctly (Anderson, Sweeney, Williams, Freeman, & Shoesmith, 2007). Although the size of the sample attempts to address the risk, there is still some residual risk that remains.

Snowball sampling removes the researcher's ability to control who has access to the questionnaire. To counteract this problem the first section of the survey has screening questions that allowed the researcher to remove unsuitable candidates from the respondents.

According to Stephens-Davidowitz (2014), people suffer from implicit or unconscious bias regardless of whether they are filling in surveys online or in person. In his paper on the difference between survey results and Google searches, it was shown that people tend to present an enhanced view of themselves even when they know that the results are anonymous.

The target population is exclusively taken from the South African investment industry. This excludes any of the potential relationships between the three measured variables in other industries. For example, sales people in other industries may display the same self-perceptions which influence the way that they pursue sales or take on new deals that may put the business at risk.

The cross sectional nature of the research limits the study to a “snapshot” view of what the respondents were perceiving at that moment of time (Oliver, 2004). This does not allow for a change of perceptions over time.

The survey questionnaire construct runs the risk of having questions that may not have been understood or may have been missing a crucial question. Even by using the pilot study to limit the number of errors in the questionnaire the researcher may have suffered from confirmation bias by distributing the pilot questionnaire to people that understand what the researcher was trying to ask instead of what the questions actually ask (Kahneman, 2011).

5 Research Results

5.1 Introduction

The chapter will outline the results that were obtained from the data gathered for the research. The results will start with an outline of the different demographics of the survey respondents to illustrate who answered the questionnaire. It will then move onto the results of each construct followed by the three hypotheses as set out in chapter three.

The data used for the results are directly from the 161 surveys collected that had useable data. The results followed the methodology set out in chapter four. The 161 useable surveys represented an 84% completion rate of the people that attempted the surveys. There were 184 responses to the initial request to participate which resulted in 23.2% response rate which is similar to the 20.2% response rate found in other investment professional studies (Deutskens et al., 2004). There were eight other surveys attempted from snowball sampling.

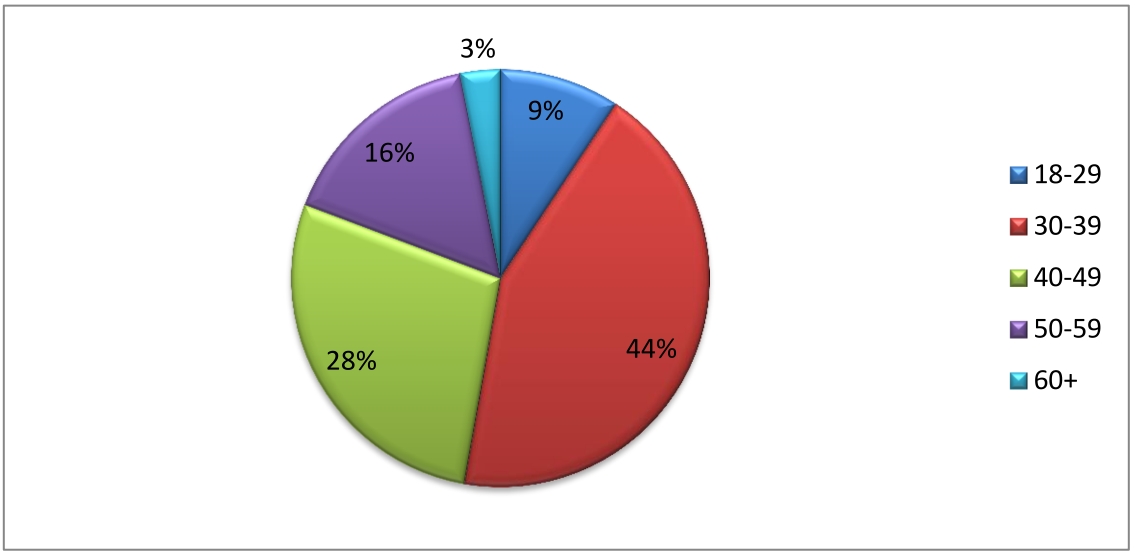
The 161 survey were provided by investment professionals in the South African investment industry that provided a homogenous sample of the targeted population. The results that follow are all based from the data provided by that sample.

5.2 Demographic Descriptions

The 161 respondents answered a total of six demographic questions that allowed the data to be segmented into age, gender, education level, fund or business type, risk level that the business or fund is targeted at, and the experience of the individual in the investment industry.

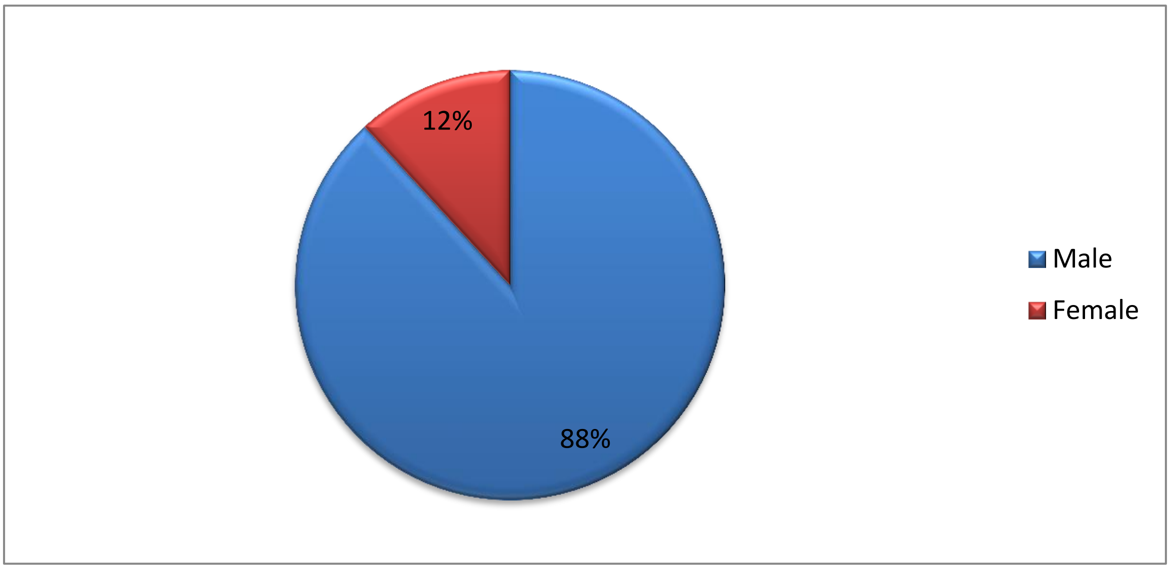
The age of the respondents was almost evenly split between those younger than 40 (53%) and those older than 40 (47%). The single biggest age group was the 30-39 demographic that had 70 respondents or 43% of the total sample.

Figure 4: Age Breakdown of Respondents



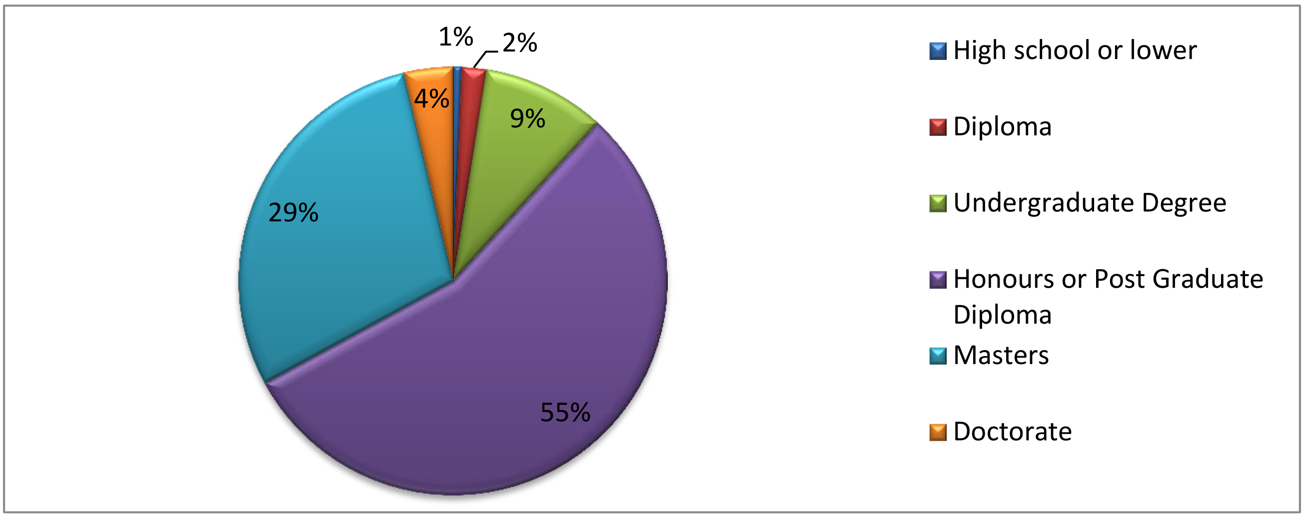
There was a large gender difference in the sample with 19 female respondents representing 12% of the overall population. There were three options given for gender specification with the third option of other. There were zero respondents that identified as non-female and non-male, which means that 82% of the sample was male

Figure 5: Gender Diversity Breakdown



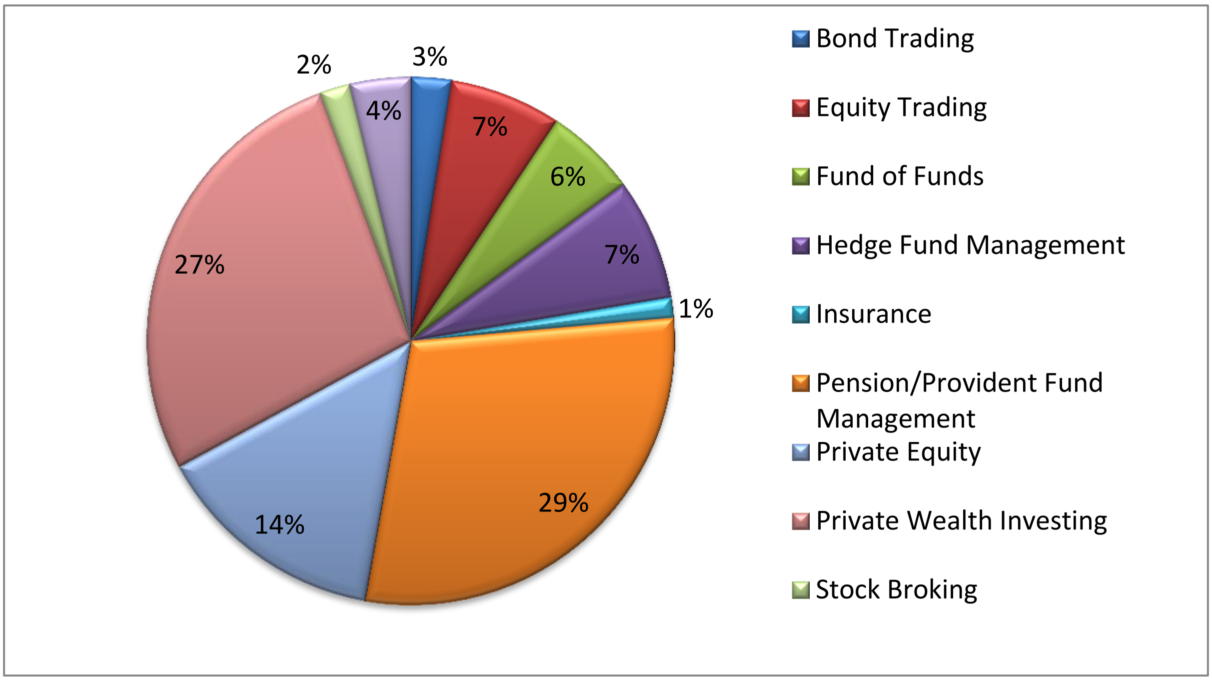
The education of the sample was relatively skewed to people that have more than an undergraduate degree (142 respondents), they represent 88% of the total sample. Interestingly there were only four respondents that had less than an undergraduate degree (2.5% of the sample).

Figure 6: Education Split



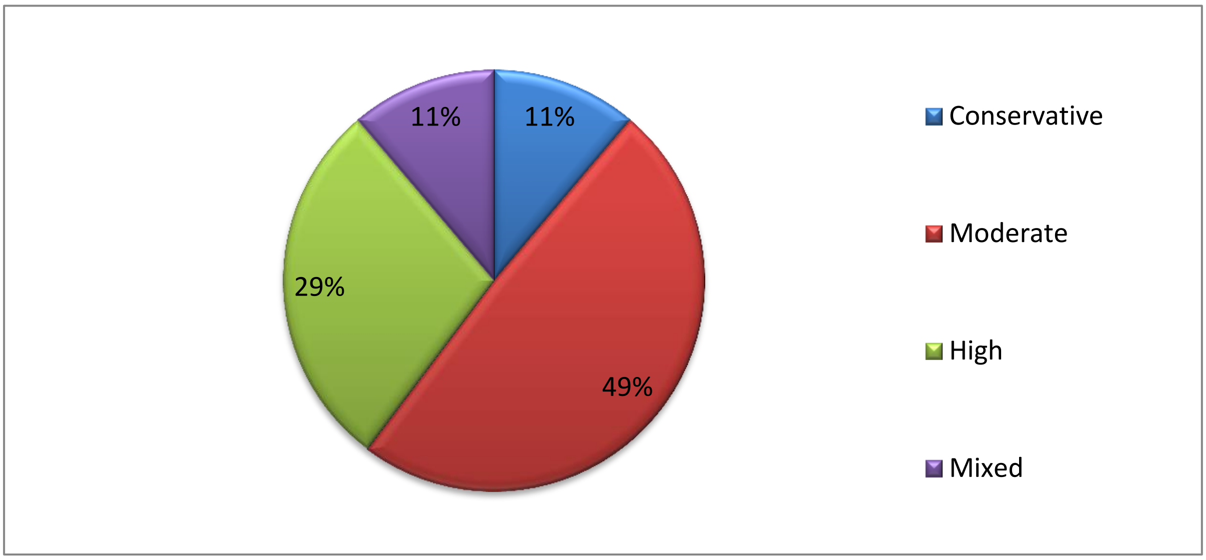
There were ten different types of investment business or fund that were represented in the sample. The two with the most representation were Pension/Provident Fund Management Firms (including unit trusts) with 47 respondents (27% of the sample), and Private Wealth Investments with 44 respondents (27% of the sample). There was an option for other, of the six respondents that answered other five specified that they were part of Venture Capital and one as Debt Capital. The catch-all option other was changed to Venture Capital and Exotics to account for the five Venture Capitalists.

Figure 7: Investment Business of Fund Type Representation



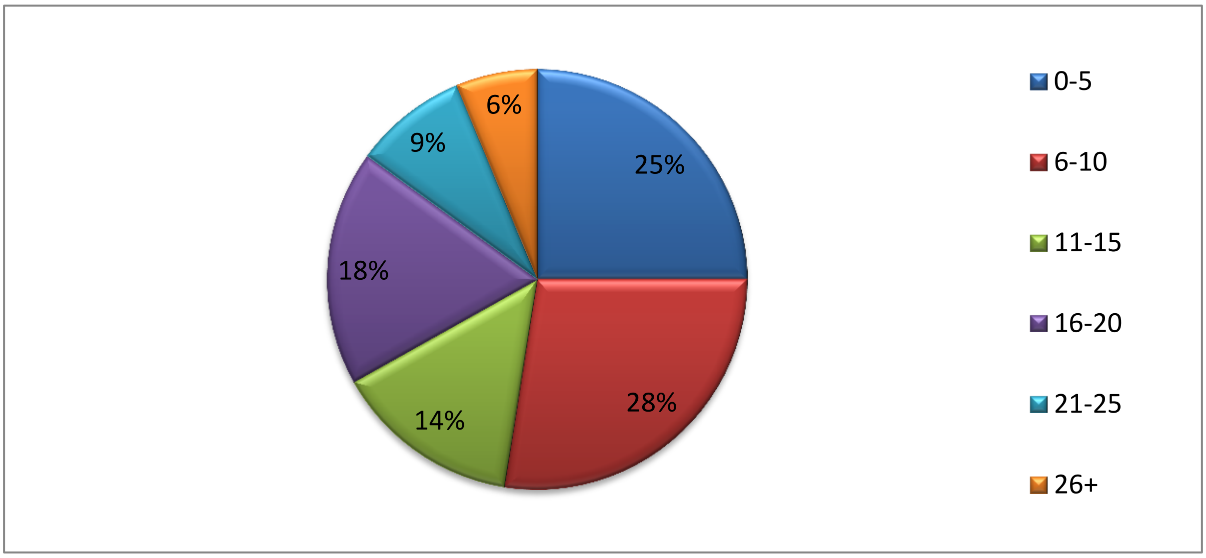
The respondents were asked what the current risk level is of the fund or business they operate in is. This showed what the determined level of risk the professionals were expected to exhibit in their investment decisions. Seventy-nine of respondents operated in the moderate risk range representing just less than half of the total sample (49%). Just over one-tenth (11%) of the sample said that the operated in a mixed risk environment, or one that is not exclusively termed high, moderate or conservative.

Figure 8: Risk Mandates Operated In



The final categorical question used to segment the sample was investment industry experience. Eighty-four respondents had ten or fewer years of experience (or 53% of the sample), and 136 respondents had less than 20 years of experience (or 85% of the sample).

Figure 9: Investment Industry Experience



5.3 Underdog Bias Construct

The underdog bias construct was based on the work by Davidai and Gilovich (2016) the construct was adapted to suit the investment industry. To check the validity and reliability of the construct the Pearson's correlation coefficient and Cronbach's alpha were both performed.

The Pearson's correlation coefficient test indicated that there were poor correlations with Q2.2, Q2.3 and Q2.5 in the construct. Initially Q2.3 and Q2.5 were removed which enabled all but one relationship between question 2.2 and 2.8 to have a significant correlation. The relationship between 2.2 and 2.8 was significantly problematic at 5.1% which was above the 5% acceptable significance level. As a result Q2.2 was removed from the construct to ensure validity. The resultant Pearson's correlations can be seen in Table 8 below.

Table 8: Underdog Bias Pearson's Correlation

Correlations

		Q2.01	Q2.04	Q2.06	Q2.07	Q2.08
Q2.01	Pearson Correlation	1	.410**	.341**	.321**	.216**
	Sig. (2-tailed)		.000	.000	.000	.006
	N	161	161	161	161	161
Q2.04	Pearson Correlation	.410**	1	.368**	.476**	.349**
	Sig. (2-tailed)	.000		.000	.000	.000
	N	161	161	161	161	161
Q2.06	Pearson Correlation	.341**	.368**	1	.307**	.516**
	Sig. (2-tailed)	.000	.000		.000	.000
	N	161	161	161	161	161
Q2.07	Pearson Correlation	.321**	.476**	.307**	1	.374**
	Sig. (2-tailed)	.000	.000	.000		.000
	N	161	161	161	161	161
Q2.08	Pearson Correlation	.216**	.349**	.516**	.374**	1
	Sig. (2-tailed)	.006	.000	.000	.000	
	N	161	161	161	161	161

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

The construct was then tested for internal consistency, which resulted in a finding in line with the acceptability margin adopted for the study (α = 0.744). Interestingly removing any of the questions would not increase the alpha of the construct (even though it was already within the guidelines).

Table 9: Underdog Bias Cronbach's Alpha

Reliability Statistics

Cronbach's Alpha	N of Items
.744	5

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
Q2.01	9.2981	18.673	.432	.725
Q2.04	9.1180	17.655	.558	.681
Q2.06	8.7453	16.878	.536	.687
Q2.07	9.3602	17.794	.507	.699
Q2.08	9.0683	17.289	.506	.699

To ensure the validity and internal consistency all data analysis on the construct going forward was done using the five questions instead of the original eight.

A single underdog bias construct score was then developed for each respondent by compiling a simple average of the five questions, this is the same method that Davidai and Gilovich (2016) used in their experiment on experimental and non-experimental accounting faculty. The overall construct was then checked for outliers, this was done using two methods first the quartile method and then the three standard deviations method. No outliers using either method were found.

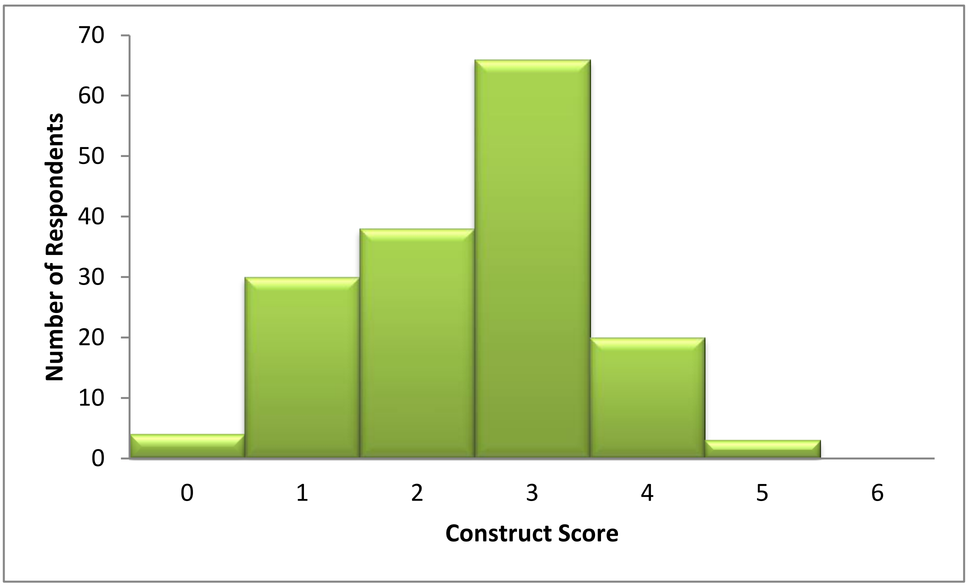
The mean of the sample (*M* = 2.28, *SD* = 1.02) was relatively low (below the midpoint) The mean was tested using a single population test with an unknown population variance to see if it was certain that the mean of the population was below the midpoint of three. The population mean can be said with 99% certainty (*p*-value <0.0001) that it is below the midpoint of three. The descriptive statistics are shown in Table 10.

Table 10: Underdog Bias Descriptive Statistics

Mean	2.28
Standard Error	0.08
Median	2.40
Mode	3.00
Standard Deviation	1.02
Sample Variance	1.04
Kurtosis	-0.25
Skewness	-0.05
Range	5.00
Minimum	0.00
Maximum	5.00
Count	161.00
Lower Quartile	1.60
Upper Quartile	3.00
Outlier Lower Limit (Quartiles)	-0.50
Outlier Upper Limit (Quartiles)	5.10
Outlier Lower Limit (Std Deviations)	-0.78
Outlier Upper Limit (Std Deviations)	5.33

The data is slightly negatively skewed as can be seen by in the histogram presentation of the construct below, but is relatively normally distributed.

Figure 10: Histogram of Underdog Bias Construct



5.3.1 Underdog Bias Demographics

Each of the demographic categories was tested using a single factor ANOVA to understand if any of the categorical variables had a mean that was statistically significantly different to the population mean. All but one category were found not to have significant differences in means.

Table 11: Underdog Bias ANOVA Summary

	F-Crit	F-Stat	p-value
Age	2.66	1.29	0.279
Gender	3.90	10.10	0.002**
Education	2.66	0.58	0.627
Risk Level	2.66	1.63	0.186
Experience	2.27	0.69	0.629
Fund Type	1.94	1.40	0.192

**. Correlation is significant at the 0.01 level
*. Correlation is significant at the 0.05 level

The gender demographic had a statistically significantly different means and comparable standard deviations (female *M* = 2.96, *SD* = 1.00, male *M* = 2.19, *SD* = 0.95).

Table 12: Underdog Bias Split by Gender

Gender	*Count*	*Mean*	*Std Dev*
Male	142.00	2.19	1.00
Female	19.00	2.96	0.95

5.4 Self-Rated Performance Construct

The self-rated performance construct measurement instrument was a combination of the scale used by Williams and Gilovich (2008) and the questions from the Core Self-Evaluation Scale (CSES) (Judge et al., 2003) that were adapted for the investment community. To determine the validity of the construct Pearson's correlation coefficient was used and then to test reliability Cronbach's alpha was used.

The Pearson's correlation coefficient showed multiple questions that had poor bivariate correlations (Q3.6, Q3.8 and Q3.12), resulting in the removal of all three questions from the data set. A second Pearson's correlation was then run which showed that Q3.9 had poor bivariate correlations (above a *p*-value >0.05) with Q3.2. To determine which variable should be removed from the data set a Cronbach's alpha was run. It showed that by removing Q3.9, the alpha would be higher (α = 0.785) than removing Q3.2 (α = 0.771). The final Pearson's correlation data table can be seen below:

Table 13: Self-Rated Performance Pearson's Correlation

Correlations

		Q3.1	Q3.2	Q3.3	Q3.4	Q3.5	Q3.7	Q3.10	Q3.11
Q3.1	Pearson Correlation	1	.288**	.305**	.332**	.196*	.382**	.442**	.436**
	Sig. (2-tailed)		.000	.000	.000	.012	.000	.000	.000
	N	162	162	162	162	162	162	162	162
Q3.2	Pearson Correlation	.288**	1	.262**	.332**	.265**	.271**	.333**	.438**
	Sig. (2-tailed)	.000		.001	.000	.001	.000	.000	.000
	N	162	162	162	162	162	162	162	162
Q3.3	Pearson Correlation	.305**	.262**	1	.261**	.270**	.526**	.241**	.395**
	Sig. (2-tailed)	.000	.001		.001	.001	.000	.002	.000
	N	162	162	162	162	162	162	162	162
Q3.4	Pearson Correlation	.332**	.332**	.261**	1	.189*	.351**	.350**	.347**
	Sig. (2-tailed)	.000	.000	.001		.016	.000	.000	.000
	N	162	162	162	162	162	162	162	162
Q3.5	Pearson Correlation	.196*	.265**	.270**	.189*	1	.339**	.274**	.405**
	Sig. (2-tailed)	.012	.001	.001	.016		.000	.000	.000
	N	162	162	162	162	162	162	162	162
Q3.7	Pearson Correlation	.382**	.271**	.526**	.351**	.339**	1	.367**	.425**
	Sig. (2-tailed)	.000	.000	.000	.000	.000		.000	.000
	N	162	162	162	162	162	162	162	162
Q3.10	Pearson Correlation	.442**	.333**	.241**	.350**	.274**	.367**	1	.345**
	Sig. (2-tailed)	.000	.000	.002	.000	.000	.000		.000
	N	162	162	162	162	162	162	162	162
Q3.11	Pearson Correlation	.436**	.438**	.395**	.347**	.405**	.425**	.345**	1
	Sig. (2-tailed)	.000	.000	.000	.000	.000	.000	.000	
	N	162	162	162	162	162	162	162	162

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

The remaining eight questions were tested for reliability using a Cronbach's alpha. The alpha was in the acceptable range for the study ($\alpha = 0.785$). The analysis on the individual questions was done to determine if removing a question would increase the reliability of the construct, removing any of the questions would have resulted in a decrease in the reliability, as seen in Table 14.

Table 14: Self-Rated Performance Cronbach's Alpha

Reliability Statistics

Cronbach's Alpha	N of Items
.785	8

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
Q3.1	123.2037	7364.014	.523	.757
Q3.2	130.2654	6603.389	.475	.770
Q3.3	120.8025	7834.482	.474	.766
Q3.4	122.0926	6822.842	.476	.766
Q3.5	111.6605	7924.549	.404	.774
Q3.7	119.5679	7265.825	.565	.750
Q3.10	121.5679	6785.253	.519	.757
Q3.11	114.2901	7449.648	.614	.748

Once the construct was in the acceptable ranges for validity and reliability, the scores were averaged to give each respondent an overall self-rated performance score. This dataset was then checked for outliers that may exist in the construct. This was done using the quartile method as well as the standard deviation method. There were no outliers detected.

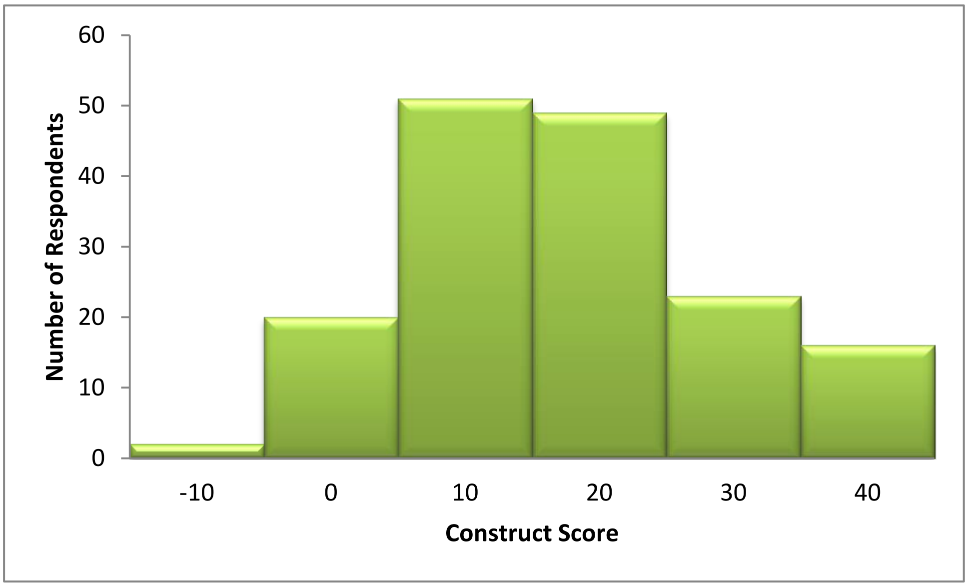
The final dataset resulted in the self-rated performance having a mean slightly above average (M = 11.89, SD = 10.21). An extensive list of the construct's descriptive statistics can be seen below in Table 15.

Table 15: Self-Rated Performance Descriptive Statistics

Mean	17.02
Standard Error	0.93
Median	16.38
Mode	27.88
Standard Deviation	11.78
Sample Variance	138.79
Kurtosis	-0.09
Skewness	0.33
Range	62.00
Minimum	-12.38
Maximum	49.63
Count	161.00
Lower Quartile	8.75
Upper Quartile	24.50
Outlier Lower Limit (Quartiles)	-14.88
Outlier Upper Limit (Quartiles)	48.13
Outlier Lower Limit (Std Deviations)	-18.33
Outlier Upper Limit (Std Deviations)	52.36

The construct was relatively normally distributed and had a slightly positive skewness to it. The histogram of the construct data set can be seen below in Figure 11.

Figure 11: Histogram of Self-Rated Performance



5.4.1 Self-Rated Performance Demographics

Multiple single factor ANOVA tests were run to determine if any of the categorical variables had a significantly different mean to the other to the overall sample. The summary of the

ANOVAS can be seen below in Table 16.

Table 16: Self-Rated Performance ANOVA Results

	F-Crit	F-Stat	p-value
Age	2.66	1.93	0.128
Gender	3.90	0.60	0.441
Education	2.66	0.75	0.523
Risk Level	2.66	0.75	0.523
Experience	2.27	3.84	0.003**
Fund Type	1.94	0.59	0.800

****. Correlation is significant at the 0.01 level**
***. Correlation is significant at the 0.05 level**

Experience showed that there was at least one category that had a statistically significantly different mean to the others. The different means of the Experience category are presented below in Table 17:

Table 17: Experience Breakdown of Self-Rated Performance

Groups	*Count*	*Mean*	*Std Dev*
0-5	40	13.24	10.15
6-10	45	15.49	11.21
11-15	23	22.21	10.09
16-20	29	17.68	11.56
21-25	14	15.31	14.13
26+	10	27.50	13.48

Although a single factor ANOVA can test for difference in means it does not determine which factor is influencing the response variable, in this case, the self-rated performance score (Wegner, 2016). To determine which factors influenced the response variable a Tukey-Kramer test was used. Tukey-Kramer is ideal for categories with different sample sizes and is still thorough (Jaccard, Becker, & Wood, 1984).

The test found that there were three relationships that were found to be significantly different (0-5 to 11-15, 0-5 to 26+, and 6-10 to 26+). The full table for the Tukey-Kramer test can be seen in Table 18. The results suggest that the 0-5 group and the 26+ group have significantly different mean than the overall industry average. Interestingly the 0-5 group have the lowest average, and the 26+ have the highest average of self-rated perception.

Table 18: Tukey-Kramer Multiple Comparison Post Hoc Test for Experience

Comparison	Diff	Std Error	q-crit	q-stat
0-5 to 6-10	2.25	1.73	4.10	1.30
0-5 to 11-15	8.97	2.09	4.10	4.29*
0-5 to 16-20	4.44	1.95	4.10	2.28
0-5 to 21-25	2.07	2.48	4.10	0.84
0-5 to 26+	14.26	2.82	4.10	5.05*
6-10 to 11-15	6.72	2.05	4.10	3.28
6-10 to 16-20	2.19	1.90	4.10	1.15
6-10 to 21-25	0.18	2.44	4.10	0.07
6-10 to 26+	12.01	2.79	4.10	4.30*
11-15 to 16-20	4.54	2.23	4.10	2.03
11-15 to 21-25	6.90	2.71	4.10	2.55
11-15 to 26+	5.29	3.02	4.10	1.75
16-20 to 21-25	2.36	2.60	4.10	0.91
16-20 to 26+	9.82	2.93	4.10	3.36
21-25 to 26+	12.19	3.31	4.10	3.69

***. Correlation is significant at the 0.05 level**

5.5 Personal Risk Propensity Construct

The personal risk propensity construct was measured using two tools. The first is the risk propensity measurement scale which was designed specifically for the research to give a more descriptive perspective of the investment industry's risk propensity. To ensure the validity of the instrument, it was compared to a risk propensity scale based on Kahneman and Tversky's (1979) prospect theory.

5.5.1 Risk Propensity Measurement Scale

The risk propensity measurement scale (RPMS) was developed with influence from the DOSPERT scale (Blais & Weber, 2006), and the work done by Hoffman, Post and Pennings (2013; 2015).

To ensure that the scale was valid and reliable a Pearson's correlation coefficient test was conducted followed by a Cronbach's alpha. The Pearson's correlation found that there were four questions that did not have statistically significant correlations. This resulted in Q4.2, Q4.3, and Q4.8 being removed from the construct. The final Pearson correlation coefficients can be seen below in Table 19.

Table 19: Risk Propensity Measurement Scale Pearson Correlations

Correlations

		Q4.1	Q4.4	Q4.6	Q4.7	Q4.9	Q4.10
Q4.1	Pearson Correlation	1	.340**	.339**	.463**	.480**	.450**
	Sig. (2-tailed)		.000	.000	.000	.000	.000
	N	161	161	161	161	161	161
Q4.4	Pearson Correlation	.340**	1	.274**	.364**	.418**	.218**
	Sig. (2-tailed)	.000		.000	.000	.000	.005
	N	161	161	161	161	161	161
Q4.6	Pearson Correlation	.339**	.274**	1	.568**	.409**	.295**
	Sig. (2-tailed)	.000	.000		.000	.000	.000
	N	161	161	161	161	161	161
Q4.7	Pearson Correlation	.463**	.364**	.568**	1	.460**	.427**
	Sig. (2-tailed)	.000	.000	.000		.000	.000
	N	161	161	161	161	161	161
Q4.9	Pearson Correlation	.480**	.418**	.409**	.460**	1	.399**
	Sig. (2-tailed)	.000	.000	.000	.000		.000
	N	161	161	161	161	161	161
Q4.10	Pearson Correlation	.450**	.218**	.295**	.427**	.399**	1
	Sig. (2-tailed)	.000	.005	.000	.000	.000	
	N	161	161	161	161	161	161

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Cronbach's alpha was then performed to check the construct for reliability. The initial test had an alpha below the target range for the study (α = 0.632). A full Cronbach's alpha test was done which showed that by removing Q4.5 the alpha would improve to inside the allowable range (α = 0.792). Further testing showed that by deleting any other items, the Cronbach's alpha would reduce, which can be seen in Table 20.

Table 20: Risk Propensity Measurement Scale Cronbach's Alpha

Reliability Statistics

Cronbach's Alpha	N of Items
.792	6

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
Q4.1	13.1242	26.109	.582	.752
Q4.4	13.8571	26.836	.437	.788
Q4.6	12.9006	26.665	.517	.767
Q4.7	13.4099	25.768	.651	.738
Q4.9	12.6087	25.265	.614	.744
Q4.10	12.3602	26.844	.488	.774

The final construct of six questions was averaged into a single mean score for each respondent. The dataset was then checked for outliers using the standard deviation and quartile methods, none were found.

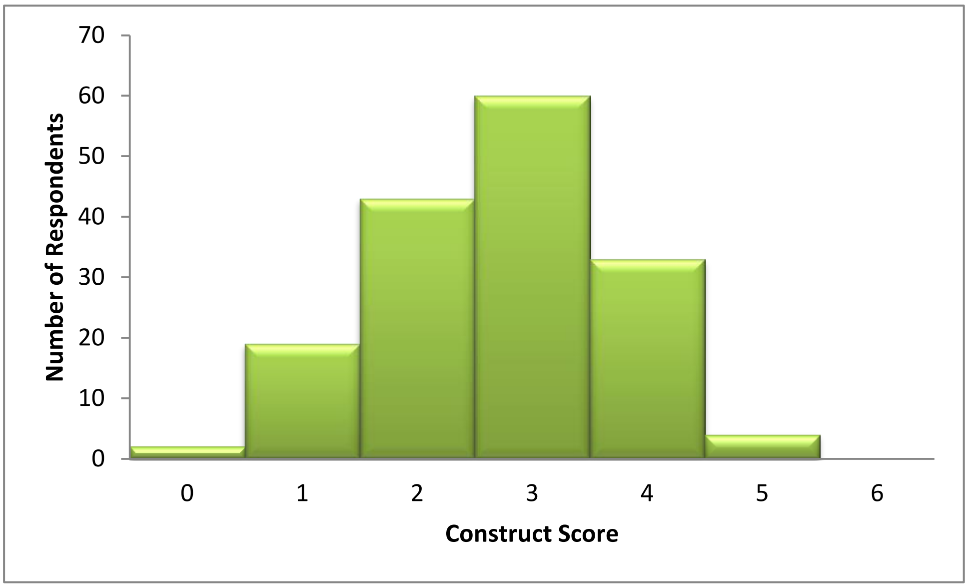
This enabled the final construct to be tested, resulting in M = 2.61 and SD = 1.00. An extended list of the descriptive statistics can be seen in Table 21.

Table 21: Risk Propensity Measurement Scale Descriptive Statistics

Mean	2.61
Standard Error	0.08
Median	2.67
Mode	2.00
Standard Deviation	1.00
Sample Variance	1.01
Kurtosis	-0.35
Skewness	-0.18
Range	4.67
Minimum	0.17
Maximum	4.83
Lower Quartile	2.00
Upper Quartile	3.33
Outlier Lower Limit (Quartiles)	0.00
Outlier Upper Limit (Quartiles)	5.33
Outlier Lower Limit (Std Deviations)	-0.40
Outlier Upper Limit (Std Deviations)	5.62

The construct was moderately negatively skewed but normally distributed, a histogram of the construct can be seen in Figure 12.

Figure 12: Risk Propensity Measurement Scale Histogram



5.5.1.1 Risk Propensity Measurement Scale Demographics

To check if there were any statistically significant different means amongst the categorical variables multiple single factor ANOVA tests where run. None of the groups were found to have statistically significant different means to one other. A summary of the ANOVA findings can be found in Table 22 below.

Table 22: RPMS ANOVA Results

	F-Crit	F-Stat	p-value
Age	2.66	0.77	0.515
Gender	3.90	0.72	0.396
Education	2.66	0.38	0.768
Risk Level	2.66	1.50	0.216
Experience	2.27	1.12	0.351
Fund Type	1.94	0.19	0.995

**. Correlation is significant at the 0.01 level
*. Correlation is significant at the 0.05 level

5.5.2 Prospect Theory Scale

The prospect theory scale that measured risk propensity was derived using the six original questions in Kahneman and Tversky's (1979) paper as well as four additional questions using the similar methodology but including a loss probability as well as a gain probability.

To validate the scale, comparisons of the results of the first six questions were compared to the results that Kahneman and Tversky (1979) found in their original paper on Prospect Theory. The comparisons can be seen below in Table 23.

Table 23: Comparison of the Original Prospect Theory to Current Study

	Options		Kahneman & Tversky		Current Study	
	A	B	A	B	A	B
Q5.01	(4000, 0.8)	(3000)	80%	20%	80%	20%
Q5.02	(4000, 0.2)	(3000, 0.25)	65%	35%	60%	40%
Q5.03	(3000, 0.9)	(6000, 0.45)	86%	14%	13%	87%
Q5.04	(-4000, 0.8)	(-3000)	92%	8%	76%	24%
Q5.05	(-4000, 0.2)	(-3000, 0.25)	42%	58%	66%	34%
Q5.06	(-3000, 0.9)	(-6000, 0.45)	92%	8%	76%	24%

There were two results that were different to the original study, Q5.3 and Q5.5, while the other four questions had relatively similar results to Kahneman and Tversky (1979).

Further analysis was done on Q5.3 to determine if it was just the sample's answer was different or if there was an alternative rationale. A comparison of the two outcomes was made using a certainty equivalent value score (Tversky & Kahneman, 1992). This showed that option B had a higher certainty equivalent score (2089), than option A (2038) which makes it more attractive than option A (using advances in prospect theory).

To create a risk level comparison, each option was re-valued using cumulative prospect theory to give each option a certainty equivalent score (Tversky & Kahneman, 1992). These can be seen in Table 24.

Table 24: Certainty Equivalent Scores

	Option A	Option B
Q5.01	2 270	3 000
Q5.02	868	737
Q5.03	2 038	2 089
Q5.04	-2 533	-3 000
Q5.05	-854	-745
Q5.06	-2 245	-2 256
Q5.07	-93	-421
Q5.08	-323	-281
Q5.09	-100	-290
Q5.10	-250	-470

The values were compared to their expected values (using expected probability) and the option with the lower probability value, but higher the expected value was deemed the safer option. The riskier option was coded with a 1 and the safer option (the highest certainty equivalent) was given a score of 0. A composite score for each respondent was given using a simple average. These composite scores became the base of the construct.

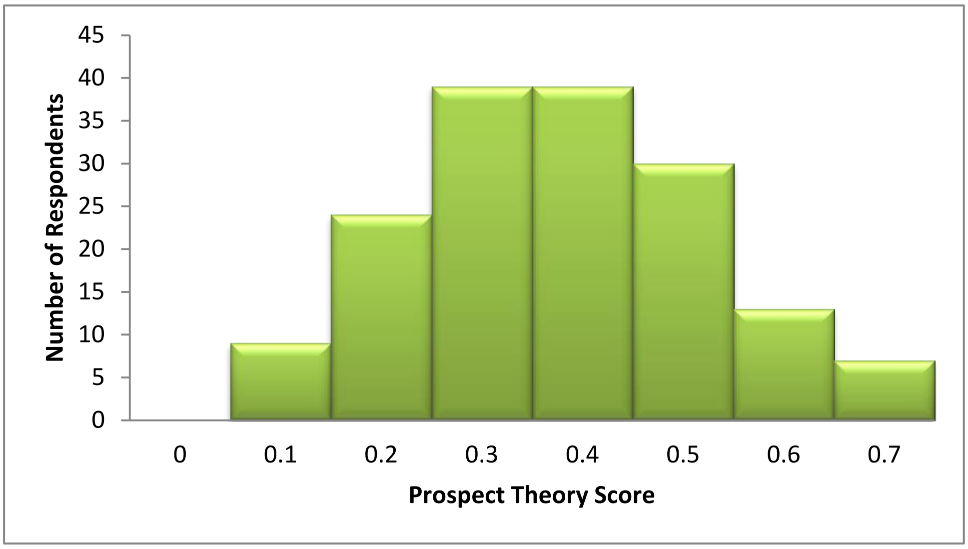
An outlier analysis was then done using both the standard deviation method as well as the quartile method. No outliers were identified in the data. The overall prospect theory scale resulted in *M* = 0.38, *SD = 0.15*. A list of the descriptive statistics can be seen below in Table 25:

Table 25: Prospect Theory Descriptive Statistics

Mean	**0.38**
Standard Error	0.01
Median	0.40
Mode	0.40
Standard Deviation	0.15
Sample Variance	0.02
Kurtosis	-0.48
Skewness	0.18
Range	0.60
Minimum	0.10
Maximum	0.70
Count	161.00
Lower Quartile	0.30
Upper Quartile	0.50
Outlier Lower Limit (Quartiles)	0.00
Outlier Upper Limit (Quartiles)	0.80
Outlier Lower Limit (Std Deviations)	-0.07
Outlier Upper Limit (Std Deviations)	0.82

The data was slightly positively skewed. This can be seen in the histogram of the data in Figure 13. The overall construct can be seen to be relatively normally distributed.

Figure 13: Prospect Theory Histogram



5.5.2.1 Prospect Theory Demographics

Each of the demographic categories were tested using a single factor ANOVA test to determine if there was a statistically significantly different mean for one of the groups in the different categories. There were no statistically significant results from the ANOVA tests (all tests had a p-value above 0.05) with the entire data set being relatively homogenous in their means, the results of the ANOVA test can be seen below in Table 26.

Table 26: Prospect Theory ANOVA Results

	F-Crit	F-Stat	p-value
Age	2.66	0.73	0.535
Gender	3.90	0.17	0.679
Education	2.66	1.33	0.267
Risk Level	2.66	1.82	0.146
Experience	2.27	0.37	0.870
Fund Type	1.94	0.99	0.450

**. Correlation is significant at the 0.01 level

*. Correlation is significant at the 0.05 level

These results are similar to the findings from the risk propensity measurement scale.

5.5.3 Comparison of Two Personal Risk Propensity Scales

To determine if the two means of the two risk propensity scales were the same or similar first the two constructs needed to be changed into scores that were comparable. To do this the construct scores for each respondent were changed into percentiles for each construct, i.e if a respondent had a score of 0.2 in the prospect theory scale it was changed to 20%, similarly a score of 3.0 in the underdog bias construct was changed to 50%.

Next, a matched pair t-test was used to determine if there was a difference in means of two constructs and, if so, how much. It was determined that there was a difference in mean of the two constructs of between 3-9% either positively or negatively. A full comparison can be seen in Table 27 below:

Table 27: Difference between RPMS and the Prospect Theory Scale

Hypothesised Difference in Mean	*p*-value
0.00 or 0%	0.001
0.02 or 2%	0.023
0.03 or 3%	0.092*
0.05 or 4%	0.637*
0.08 or 8%	0.177*
0.09 or 9%	0.051*
0.10 or 10%	0.011

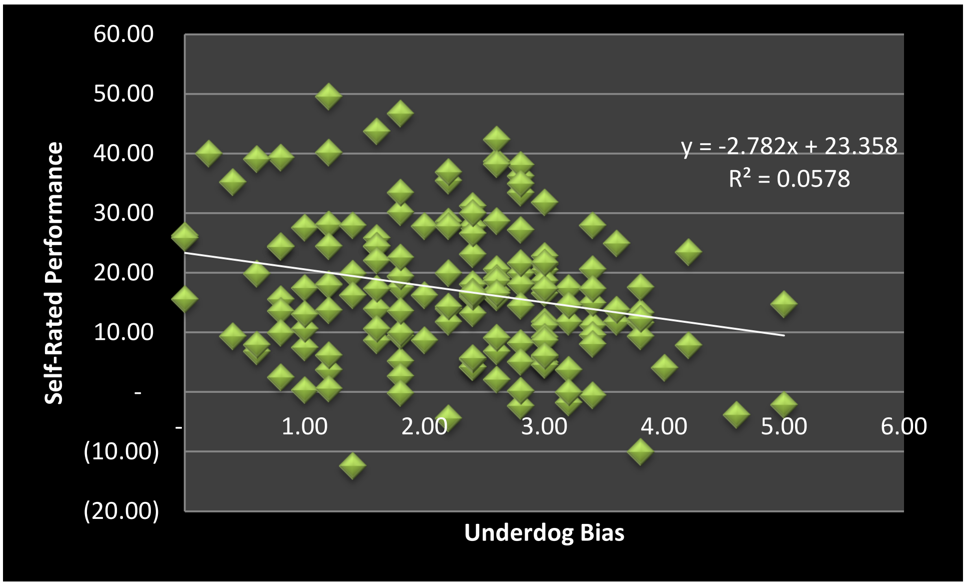
*. Correlation is significant at the 0.05 level

Although the difference of means is not high it does mean that there is a slight difference in the measurement of the two scales. A correlation analysis was done to determine if there was a relationship between the two scales. The analysis showed that there was a positive correlation, although at a 10% confidence interval ($r(159) = 0.14$, $p = 0.086$) This is a weak correlation but it does show that the two variables are related.

5.6 Hypothesis One: Underdog Bias and Self-Rated Performance

To understand if there was a positive correlation between the underdog bias construct and the self-rated performance construct regression analysis was performed. A scatterplot was done to visually understand if there was a definite relationship between the two constructs, which can be seen in Figure 14 below.

Figure 14: Scatterplot of Underdog Bias and Self-Rated Performance



Next, a correlation of the two constructs was run which showed that they are weakly negatively correlated ($r(159) = -0.24$, $p < 0.01$).

Lastly, a full regression model was run. This showed a very weak association between underdog bias and self-rated performance ($R^2 = 0.0578$, $F(1,159) = 9.76$, $p < 0.01$).

The result showed that underdog bias is weakly correlated to self-rated performance. This means that for every point movement in the average score for underdog bias (or for every standard deviation) there is a 2.782 point movement (or one fifth of a standard deviation) in the self-rated performance construct in the opposite direction. The full regression test can be seen below in Table 28.

Table 28: Regression Model of Underdog Bias and Self-Rated Performance

Regression Statistics	
Multiple R	0.240
R Square	0.058
Adjusted R Square	0.052
Standard Error	11.471
Observations	161

ANOVA					
	df	*SS*	*MS*	*F*	*P-value*
Regression	1	1 284	1 284	9.76	0.00
Residual	159	20 922	132		
Total	160	22 207			

	Coefficients	***SE***	***t Stat***	***P-value***	***Lower 95%***	***Upper 95%***
Intercept	23.36	2.22	10.51	0.000	18.97	27.75
Underdog Bias	-2.78	0.89	-3.12	0.002	-4.54	-1.02

This means that Hypothesis One which states that underdog bias is positively correlated to self-rated performance is not supported. The null hypothesis is accepted.

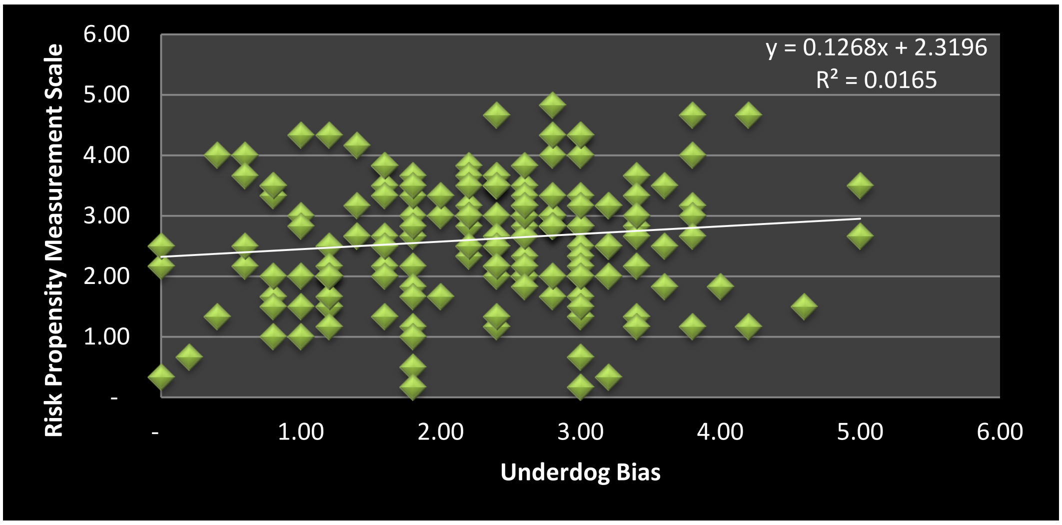
5.7 Hypothesis Two: Underdog Bias and Personal Risk Propensity

To understand if there is a correlation between underdog bias and personal risk propensity regression analysis will be run on both personal risk propensity constructs. The first will be an analysis of the relationship between the RPMS and underdog bias and the second will be an analysis of the relationship between risk propensity measured by the prospect theory scale and underdog bias. To ensure consistency the same analysis has been used in both experiments.

5.7.1 Underdog Bias and the Risk Propensity Measurement Scale

To determine the relationship between underdog bias and the RPMS constructs a scatterplot was done to understand the relationship graphically, this can be seen below in Figure 15.

Figure 15: Scatterplot of Underdog Bias and RPMS



Next, a correlation analysis was done between the two constructs. There was a very weak correlation positive correlation between the two constructs ($r(159) = 0.129$, $p = 0.104$).

Lastly, a full regression analysis was run. The regression analysis showed that there was no statistically significant relationship between underdog bias and the RPMS construct. This means that underdog bias is not a predictor of the RPMS scale at a 95% certainty level. The full regression analysis results can be seen in Table 29 below.

Table 29: Regression Analysis of Underdog Bias and RPMS

Regression Statistics	
Multiple R	0.13
R Square	0.02
Adjusted R Square	0.01
Standard Error	1.00
Observations	161

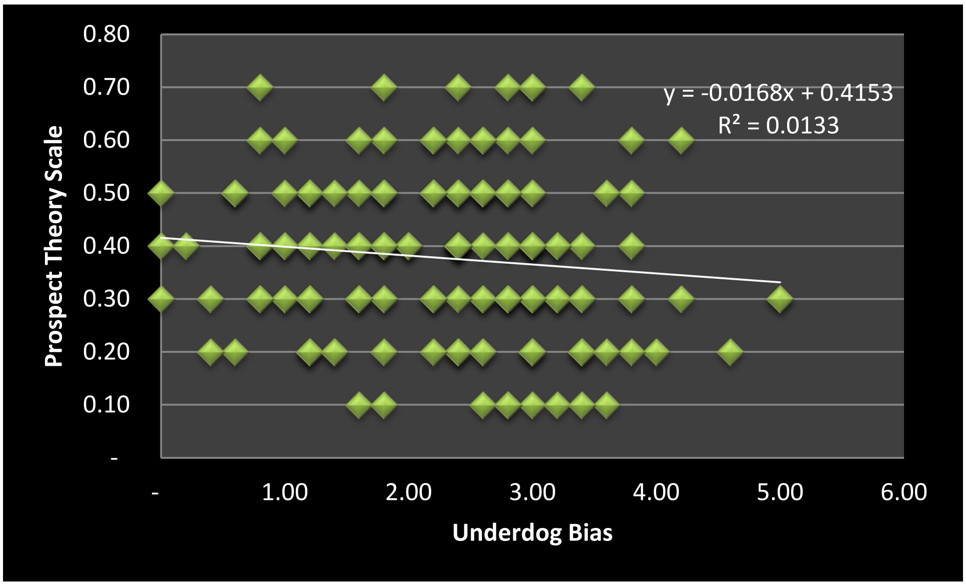
ANOVA					
	df	*SS*	*MS*	*F*	*P-value*
Regression	1	2.67	2.67	2.67	0.104
Residual	159	158.62	1.00		
Total	160	161.29			

Hypothesis two (option A) is not supported as the relationship between underdog bias and personal risk propensity as measured by the RPMS is statistically insignificant ($p>0.05$). The null hypothesis is accepted.

5.7.2 Underdog Bias and Prospect Theory

The same structure was used to test the relationship between underdog bias and the prospect theory scale as was used between underdog bias and the RPMS. A scatter plot diagram was used to test the relationship first. This can be seen in Figure 16.

Figure 16: Scatterplot of Underdog Bias and Prospect Theory



Next a correlation was performed. This resulted in a very weak negative correlation (*r*(159) = -0.115, *p* = 0.15).

Lastly, a full regression model was run. The model showed there was no statistically significant relationship between the two constructs (the *p*-value was well above the 0.05 threshold). This means that underdog bias is not a good predictor of risk propensity using the prospect theory scale. The full regression analysis can be seen below in Table 30.

Table 30: Regression Analysis of Underdog Bias and Prospect Theory

Regression Statistics	
Multiple R	0.115
R Square	0.013
Adjusted R Square	0.007
Standard Error	1.015
Observations	161

ANOVA					
	df	*SS*	*MS*	*F*	*P-value*
Regression	1	2.20	2.20	2.14	0.15
Residual	159	163.74	1.03		
Total	160	165.94			

Hypothesis two (option B) is not supported as there is no statistically significant relationship between underdog bias and personal risk propensity as measured by prospect theory (*p*>0.05), the null hypothesis is accepted.

As Hypothesis two: option A and B have both not been supported, it is fair to say that there is no statistically significant relationship between underdog bias and personal risk propensity.

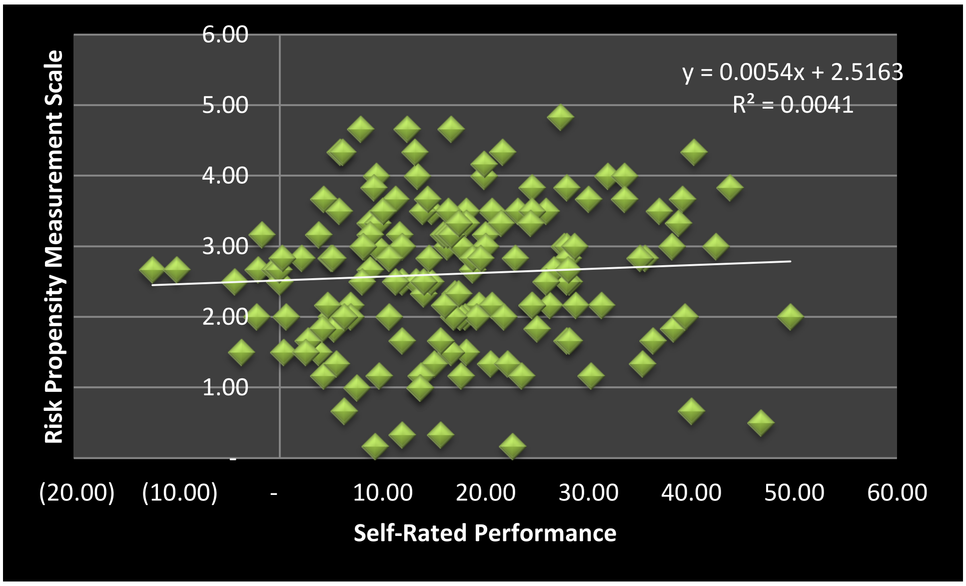
5.8 Hypothesis Three: Self-Rated Performance and Personal Risk Propensity

Hypothesis three attempted to understand if there was a positive correlation between self-rated performance and personal risk propensity. This was measured using two different regression models. The first regression model was done to understand the relationship between self-rated performance and personal risk propensity measured by RPMS. The second was done similarly but between self-rated performance and personal risk propensity as measured by the prospect theory scale.

5.8.1 Self-Rated Performance and the Risk Measurement Scale

To understand the relationship between the two constructs a scatter plot diagram was done to understand if there were any observable relationships. This can be seen in Figure 17 below:

Figure 17: Scatterplot Diagram of Self-Rated Performance and RPMS



Next, a correlation analysis was done, this showed that the two constructs were very weakly positively correlated ($r(159) = 0.064$, $p = 0.42$).

Lastly, a full regression analysis was completed. The model was found to be statistically insignificant ($p>0.05$) which means that there is no statistically significant relationship between self-rated performance and RPMS. The full regression model can be seen in Table

31 below.

Table 31: Regression Model of Self-Rated Performance and RPMS

Regression Statistics	
Multiple R	0.064
R Square	0.0041
Adjusted R Square	-0.00
Standard Error	1.01
Observations	161

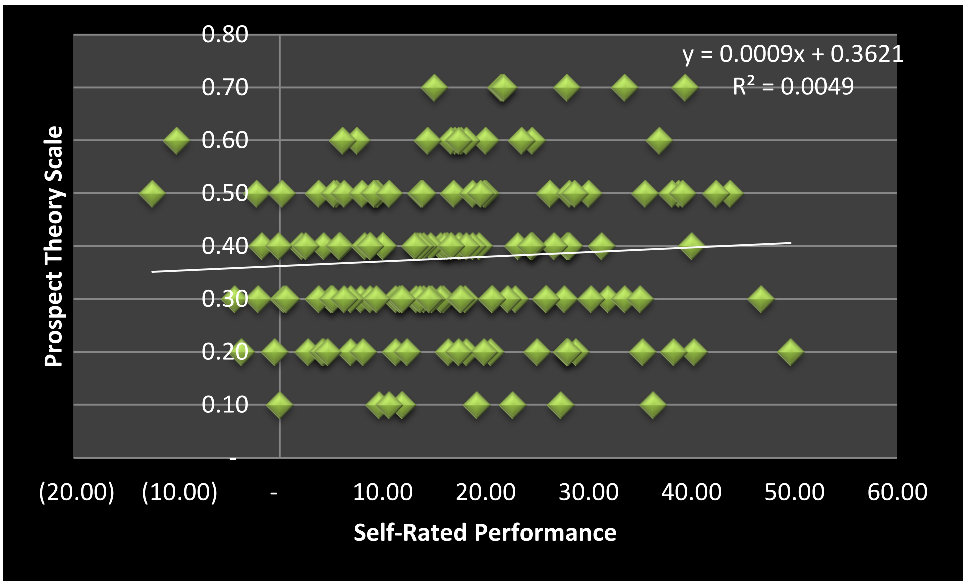
ANOVA					
	df	*SS*	*MS*	*F*	*P-value*
Regression	1	0.66	0.66	0.65	0.42
Residual	159	160.64	1.01		
Total	160	161.29			

The no statistically significant relationship between self-rated performance and risk propensity as measured by the RPMS which mean that Hypothesis Three (Option A) is not supported (*p*>0.05), the null hypothesis is accepted.

5.8.2 Self-Rated Performance and Prospect Theory

To test the relationship between self-rated performance and risk propensity as measured by the prospect theory scale a regression analysis was followed (the same as the one used for self-rated performance and RPMS). First, a scatter plot diagram was used to visually determine the relationship between the constructs. This can be seen in Figure 18:

Figure 18: Scatterplot Diagram of Self-Rated Performance and Prospect Theory



Next, a correlation test was run which showed that the two constructs were very marginally correlated ($r(159) = 0.070$, $p = 0.38$).

Finally, a full regression model was run. The test found that the two constructs have a statistically insignificant relationship ($p>0.05$. This means that self-rated performance is a not a significant predictor of risk propensity as measured by the prospect theory scale. The full regression model can be seen below in Table 32 below.

Table 32: Regression Analysis of Self-Rated Performance and Prospect Theory

Regression Statistics	
Multiple R	0.0697
R Square	0.0049
Adjusted R Square	0.00
Standard Error	11.79
Observations	161

ANOVA					
	df	*SS*	*MS*	*F*	*P-value*
Regression	1	108	108	0.78	0.38
Residual	159	22099	139		
Total	160	22207			

Hypothesis Three (Option B) is not supported as there is no statistically significant relationship between self-rated performance and personal risk propensity as measured by prospect theory ($p>0.05$). The null hypothesis is accepted.

This means that Hypothesis Three Options A and B are both rejected, in favour of the null hypothesis. There is no statistically significant relationship between self-rated performance and personal risk propensity.

5.9 Conclusion

The study had some interesting results from the target population. The breakdown of the demographics was very male dominated, but overall the population showed an impressive level of education.

The underdog bias construct came out lower than expected, and interestingly females did show a statistically higher level of underdog bias than males. Self-rated performance, RPMS and risk propensity as measured by the prospect theory scale had results that were on par with expectation. Self-rated performance showed that there were statistically different means from the categories with the respondents with the least experience and respondents with the most experience.

The personal risk propensity construct had two measures both of which came out with similar results (within 3-9% of one another). The RPMS also had relatively similar results to the DOSPERT scale when it was tested.

Hypothesis one found that there was no positive correlation between underdog bias and self-rated performance. In fact, just the opposite was found as there was a weak, but statistically significant, negative correlation between the constructs.

Hypothesis two found that there was no statistically significant relationship between underdog bias and either of the risk propensity measures, which enabled the conclusion that there is no statistically significant relationship between underdog bias and personal risk propensity.

Hypothesis three found that there was no statistically significant relationship between self-rated performance and either of the risk propensity measures. This shows that there is not a positive correlation between self-rated performance and personal risk propensity.

6 Discussion

6.1 Introduction

The chapter will go into a discussion on the results of the research. It will start by going through the demographics of the survey, followed by the findings of the different constructs and then finally tackle the three hypothesis and their outcomes.

The discussion will give a broad reasoning or understanding of the test results and attempt to explain some of the more interesting findings from the research.

6.2 Demographic Descriptions

The six different demographic categories enabled the study to test the sample to see if there are any differences between certain variables that may affect the outcome of the research. For example, the ability to compare experience as well as age give the research insight into whether or not there is a difference in the overconfidence of individuals with more experience to the overall sample, or if there is a significant difference between the underdog bias of younger versus older people.

To test these differences, we first need to understand the breakdown of the demographics of the sample. The age bracket of the sample was predominantly (71%) between 30-49 years old. This may have been because of the identified population being individuals that are actively involved in the decision making process of the investments at a firm. This means the individuals targeted are relatively senior in their respective organisations. This does not necessarily explain why the respondents dropped off after 49. This may be because of promotion (into a role that manages the fund managers but no longer is directly involved in investment decisions), or it may be from investment professionals leaving the profession as their career changes, finally it may simply be due to older individuals not responding to the questionnaire.

There was a strong gender bias towards male respondents in the sample, 142 of the 161 useable surveys. This meant that the respondents that identified as female only constituted 12% of the sample. Although small, this is not necessarily unrepresentative of the investment industry that continues to be male dominated. Hoffman, Post and Pennings (2013) found with very similar purposive sampling technique and a similar target population (although in the Netherlands) that their sample consisted of 8% female respondents.

The educational category was interesting from the perspective of the how well educated the investment professionals were. One hundred and forty-two of the respondents (the same number as males in the sample but not the same people) had more than an undergraduate degree, with more than 30% of the sample having a masters or higher. Only 2.4% of the sample, or 4 respondents, had less than an undergraduate degree. This shows the high level of education needed to be part of the investment industry, which can also be seen as a high barrier of entry to joining the industry.

There was a good mix of different types of investment funds and businesses that the sample respondents were part of. The three highest representations were pension/provident funds (including unit trusts) (29% of the sample), private wealth investment houses (27% of the samples), and private equity firms (14% of the survey). They were likely to be the highest representation of the study because of two factors. The first is that the three industries are the largest and most public recognisable employers of investment professionals, making them readily accessible to being contacted. Secondly, and due in large part to the first factor, they were the three industries that the researcher contacted most as part of the purposive sampling.

The last categorical sample is experience in the investment industry. Just more than half (53%) of the respondents had less than ten years of experience in the industry. This is interesting because of the targeted population of the research. As all the respondents are decision makers in the respective firms it shows that they get to the decision making level of their careers relatively early on. This may be mitigated by the high barriers of entry into the industry as shown by the education level of the sample.

The sample of the population (which can be assumed to be representative of the population due to the purposive sampling method used and the relative size of the sample), through the categorical variables, have shown that the industry is male dominated, is very well educated (at least in the traditional sense), is typically below 50 years old, and has less than 15 years of experience.

6.3 Underdog Bias Construct

The question combination for underdog bias was adapted from the work of Davidai and Gilovich (2016). Their studies were done on sports fans, American voters, siblings, university students, and university accounting faculty. They had not as yet studied the effect in the investment professionals.

In all of Davidai and Gilovich’s studies, they found that people tend to have a bias towards facing more difficult headwinds than the tailwinds they receive. The underdog bias construct

(*M* = 2.28, *SD* = 1.02) was slightly below the midpoint of the Likert scale (a score of 3). This represented a compound score of below what would be expected if individuals felt they faced significantly higher headwinds than tailwinds they receive. This means that on average the investment professionals did not feel as though others had a significant advantage over them in the investment industry.

Interestingly the mean of the sample was almost a full standard deviation below the midpoint. This shows that not only does the average investment professional think that face more benefits than headwinds, but the bulk of the sample felt the same way.

There average score of each question was relatively homogenous with the difference between the highest individual question mean score (Q2.6 – I have to work harder than others to get the recognition I deserve – *M* = 2.65, *SD* = 1.53) and the lowest individual question mean score (Q2.7 – My investors tend to blame me more harshly than others when the market takes a downturn – *M* = 2.04, *SD* = 1.43) is less than a single point difference. Interestingly every individual question had a mean well below the midpoint of the scale. This does make sense considering the relatively high Pearson's correlation but does also show that overall, the individual indicators the investment professionals did not think that they faced stiffer headwinds than the tailwinds they receive.

One potential reason for this may have been caused by the adjusting of the questions by the researcher to fit the investment environment. But this is an acceptable practice and was done by the Davidai and Gilovich (2016) where they used adjusted questions for each different experiment to suit the audience and who was participating in it. For example when using academics as participants were asked specifically around four different elements of an academic career: publishing, finding a job, getting tenure and receiving research grants. To attempt to recreate this, the underdog bias section of the questionnaire focussed on themes in the investment community like investor relations, research, company access and support from inside the investment community.

The other potential difference in this study compared to the Davidai and Gilovich (2016) study may have been that in most of the Davidai and Gilovich's experiments they used specific comparisons. For example, in the sibling study, they asked participants to compare themselves to their brother or sister. Although this was true for most of the experiments, the sports fan experiment was specifically designed so that the participants were not explicitly asked to compare themselves to another. The sports fans were found to face significant headwinds compared to the tailwinds they receive. This means that even in an environment where there was no framing of the context (Kahneman, 2011) to enhance underdog bias there was still a significant feeling of being more hard done than others.

The underdog bias construct has a boundary condition that may have played a part in the unexpected result. Individuals tend to be more aware of the benefits they receive from other individuals than they are of anything else (Davidai & Gilovich, 2016). The financial industry is service industries where the extra leeway received from an investor (Q2.2), or recognition given by a manager (Q2.10) may result in the benefits (or tailwinds) that the professionals receive come from people.

The second issue that may trigger the boundary condition is that the barriers of headwinds that the professionals face are typically from the market. These may be perceived to be outside the locus of control of the investment professional. There is still the possibility (at least in the professional's mind) that under the same circumstances given the same information others would have made the same decision. This is called negative minimisation where poor decisions are reasoned out to where they become neutral or even positive (Taylor, 1991). The fact the headwinds or barriers of the decisions are only felt a while after the decisions are made supports the view of Rozin and Royzman (2001) where there is a positivity bias to an individual's memory. Finding the boundary condition in underdog bias would be a unique finding and to be sure that this is the result a deeper examination of the population and similar ones will be discussed in the further studies.

A less technical, but simpler explanation may be that the South African investment community do not feel that they suffer from underdog bias compared to others. The result would be interesting as this would be opposite to the findings of the Davidai and Gilovich (2016) study. It may represent a very specific community that seems to feel their tailwinds more than their headwinds.

This finding is pertinent in two ways, firstly that South African investment community may be an exception compared to other sectors of society. Secondly, and more importantly, in a South African context that has historically been divided and still suffers from societal divisions, the investment community has potentially managed to find a way through those divisions. Sceptics may say that the sample is not representative of the overall population, the dissertation does not deny this, but it does not rule out the possibility that there is some factor that the investment community has that allows it to not feel underdog bias in the same way as other populations.

6.3.1 Underdog Bias Demographics

The only demographic that had significantly different results for the underdog bias construct was the gender category. Females felt they faced significantly stiffer headwinds compared to what males experienced. Although the female score (*M* = 2.96, *SD* = 0.96) was still slightly below the midpoint (3) it does show that the females in the study felt that they feel that their benefits versus barriers are almost equal in strength, whereas males scored well below the midpoint (*M* = 2.19, *SD* = 1.00).

One possible explanation for this may be the difficulty that females face in a workforce that is male dominated. The male dominance of the industry can be seen in the significantly lower number of female respondents in the survey (12%) which was in line with other studies of similar populations (Hoffmann et al., 2013).

6.4 Self-Rated Performance Construct

The self-rated performance construct's questions were adapted from the Core-Self Evaluation Scale (CSES) (Judge et al., 2003). The CSES was designed to combine specific individual measures for four specific traits (self-esteem, generalised self-efficacy, neuroticism, and locus of control) into one tool for the working environment, or in another sense the CSES was designed so that individuals could rate themselves according to the four traits. The questions were adapted for this study from a general sense to be more specific to the investment industry.

The second part of the adaption was to utilise the same tool that Williams and Gilovich (2008) used to ensure that the respondents compared themselves to their perception of average. This combination was crucial for the testing tool as it meant that there was an anchor position in respondents mind as to where the average person in their industry operates compared to themselves (Festinger, 1954).

The change in the questions resulted in the Pearson's correlation coefficient test removing four questions from the construct. Although unfortunate to remove some of the questions the construct still had a good mix of reverse scored (three) and normal scored (five) questions.

The mean score of the construct (*M* = 17.02, *SD* = 11.78) showed that the average respondent rated themselves in the 67th percentile of the population, this is close to the work of Williams and Gilovich (2008) who found people typically rate themselves "roughly at the 60th or 65th percentile" (p.1121). The Geunther and Alicke (2010) study on the better than average effect showed that respondents rated themselves between the 65th to 75th percentiles. Both the studies did use university students and although a university is a competitive environment the population does not necessarily represent the working environment.

The Judge, Erez, Bono, and Thoresen (2003) paper that developed the CSES did use respondents from a work environment in two of their studies. Both of these studies showed respondents scored themselves above average in their self-evaluations even though it was not designed to test respondent's comparison. The studies on the respondents that were active in the workforce at the time showed individual's scoring themselves between the 77th and 79th percentiles, on average.

The self-rated performance construct had a mean score (*M* = 17.02, *SD* = 11.78) is comparable to other studies and is in line with the expectations of a general view of self-rated performance. Perhaps, what is interesting is that the stereotypical view of the investment professional is one where the hubris of the industry is particularly high. If the stereotype was followed it may have not been surprising if the self-rated performance construct was slightly above the other studies.

It is important to note that the investment professionals compared themselves to their perception of the average investment professional, not to the average member of the public. Their hubris that the industry is known for may come out if they investment professional is asked to compare themselves to the "man on the street."

6.4.1 Self-Rated Performance Demographics

There was only one categorical factor that showed a statistically significant difference in means, experience. There was no statistically significant difference in self-rated performance between genders which was interesting compared to the underdog bias construct.

What was interesting to note is that of all the different categorical groupings that were tested not one of the groups had a mean that was less than 12 or the 62nd percentile. This means that no group felt that they were less than average overall but rather they were all consistently above average, regardless of demographic category.

From the Tukey-Kramer test performed on the experience category there were three significant relationships that showed a difference in means, with two groups as the common factors in the relationships. The first was the low score set by those in the industry with the least experience, the 0-5 year group (*M* = 13.24, *SD* = 10.15) and the second was the highest score set by the group with the most experience 26+ years (*M* = 27.50, *SD* = 13.48).

Taken at face value this means that individuals with less experience are less sure of themselves and have a lesser opinion of their performance compared to others, rating in the 63rd percentile. While professionals that have the most experience rate themselves highly against their peers in the 78th percentile. This is consistent with Tversky and Kahneman's (1973) availability heuristic where the pair described the availability of success of the past may lead to someone thinking they will succeed in the future.

The respondents of the survey may argue that the reason they are still part of the industry 26+ years later is because they have managed to be successful for many years. They would have been removed from the industry if they were not successful.

Kahneman and Klein (2009) argued that to become an expert or to have expertise in a subject then that activity needs to be highly repeatable so that hours of practice in the same or very similar circumstances lead to a level of expertise. Kahneman (2011) specifically dealt with the unpredictability of the investment market where expertise is very difficult or unlikely to occur. At the very least the randomness of the success is a higher indicator than expertise over a long period of time.

This shows that even though the individual's with the most experience felt that they were experts in the industry, they are unlikely to be. This is also very typical of hindsight bias where past results, or in this case overconfidence from success in the past is not necessarily a good predictor of success in the future (Fischhoff, 1975).

The low average score of the 0-5 year group could be a result of the inverse of the 25+ year group. The group, in general, may not feel like they have had the time to get the expertise that the respondents with more experience have. This may not be the case of expertise but may be a factor of the lesser experienced respondents not having enough time to develop the biases that the more experienced have.

6.5 Personal Risk Propensity Construct

The personal risk propensity construct was divided into two separate scales; both measure similar things. The first is the risk propensity measurement scale (RPMS) which was developed specifically to suit the needs of the research, and the second is a risk propensity measurement instrument based on a slight adaptation of prospect theory from Kahneman and Tversky's (1979) original paper on the topic.

The rationale for using two different scales to measure personal risk propensity is because the researcher could not identify a scale that would measure the risk propensity specifically for investment professionals. The closest was the DOSPERT scale which together with the work specifically based on investment professional risk formed the base of the new scale. To make sure that the scale was in line with existing risk measurements a scale using prospect theory was also tested in the research.

6.5.1 Risk Propensity Measurement Scale

The concept for the scale was to develop a tool that is similar to the DOSPERT scale (Blais & Weber, 2006) specifically for the investment industry without the dependency of the market perception that the Hoffman, Post and Pennings (2013; 2015) work is reliant on.

The DOSPERT scale was focussed on the behaviour around general populations. It focussed on the five areas of ethics, finances, health and safety, recreational activities, and social activities. Initially, it was thought that the questions could be used just for the financial areas but in early screening of the investment industry all scores were likely to show high risk using just those measures. This may have been because they are sensitised to some of the financial activities that may be perceived to be risky in the rest of the general adult population.

This high scoring in the DOSPERT financial scale may be due to the familiarity from the investment industry associates with taking financial risk, which may lead them to believe that they understand or at least can cope with the risk better than others (Heath & Tversky, 1991).

The second influence on the Risk Measurement Propensity Scale (RPMS) was from the work of two studies on a similar target population in the investment industry. Those studies also looked at how different decisions are influenced by the risk the investor has taken on or will take on (Hoffmann et al., 2013; 2015). The scale that the study used was risk tolerance (which was similar to risk propensity), but it was not comprehensive enough to use as a standalone scale.

The concept of the DOSPERT was then combined with the risk tolerance scale from Hoffman, Post and Pennings (2013; 2015) and adapted to create the Risk Propensity Measurement Scale.

When checking for validity and reliability the Pearson's correlation coefficient test and the Cronbach's alpha test removed the three reversed questions (Q4.3, Q4.5, and Q4.8) from the scale as well as one other question (Q4.2). This is slightly worrying that the reverse questions may not have had the same effect on confidence in reward from the investors that the questions on risk had. After the questions were removed, the scale did have a high validity (all Pearson correlations were above the 1% significance) and reliability ($\alpha = 0.792$) test statistics.

The RPMS construct gave the study a mean (*M* = 2.62, *SD* = 1.01) that is below the median level in the rating scale (3), but does not necessarily indicate that the investment community is not risk seeking, especially as the midpoint is less than a fourth of a standard deviation away from the mean score. To determine the level of risk propensity in the investment community the RPMS would need to be tested in a different population to use as a base rate (i.e. a representative sample of the South African population). What the construct does allow us to do is compare it to similar tests and their results.

The Hoffman, Post and Pennings (2015) study also used a 7 point Likert scale as a measurement instrument. The average score of the longitudinal study found that the investors had an average mean of 3.933. This score is more than a standard deviation (in this study) higher than the RPMS score. An interesting aspect to note from the Hoffman, Post and Pennings (2015) was that the return expectation, or the optimism from the investors that the market will show favourable returns, had an average mean over the period of 3.929. Importantly the Hoffman study showed that the risk tolerance of investors and the risk expectation were highly correlated. Perhaps, the high return expectation resulted in a higher risk tolerance from investors.

This may mean that the investors were highly confident or overconfident in their predictions of the market which meant that their perception of the risk that they were taking on was lower than normal. This echoes the finding by Slovic, Fischhoff, Lichtenstein and Roe (1981). The current study did not test return expectation of the respondents but the data collection period was on the backdrop of a 32 year low in business confidence in South Africa (Fin24, 2017; Trading Economics, 2018), which may have caused the lower score in the RPMS.

The revised DOSPERT scale tests were run in two different populations both based in Canada (Weber, Blais, & Betz, 2002). The first was a random sample of English speaking adults and the second a random sample of French speaking adults. The mean score for the financial risk taking part of the DOSPERT was 49% and 44% respectively, this is in comparison to the RPMS of 44%. The relative scores, although testing different populations and slightly different things, are comparably similar.

6.5.1.1 Risk Propensity Measurement Scale Demographics

There were no significantly different means found in the testing of the categorical variables in the RMPS construct. This means all the respondents had a statistical similar mean that was similar to the population as a whole.

Although this is a good finding as it shows that the sample is heterogeneous, there may have been an expectation that the investors with the most experience are happy to take on more risk (Heath & Tversky, 1991; Hoffmann et al., 2015) and that investors with little experience also take on more risk (Goetzmann & Kumar, 2008). The study did find that the investment professionals with the least experience (0-5 years) and the most experience (26+ years) had the highest mean scores ($M_{0\text{-}5}$ = 2.60 and M_{26+} = 2.59), but neither were statistically significantly different when compared to the other means.

Recent findings have shown that there can be a difference in risk between the genders with females tending to be more risk averse than males (Ch'ng, 2017). Interestingly the RPMS found that females were no different to men in their risk propensity and even had a very slightly higher average score although not statistically significantly different (M_f = 2.77 and M_m = 2.56).

6.5.2 Prospect Theory Scale

To measure risk propensity using prospect theory the scale was taken directly from the work of Kahneman and Tversky (1979). The first six questions were the same six questions from their study. The last four were designed in a similar vein using a similar design method but incorporated a potential loss as well as a gain.

To check the validity of the study a comparison of the first six questions was done to the original work. There results for all questions barring two (with Q5.3 being significantly different) were very similar.

The difference in Q5.3 can be accounted for based on the population that was being asked the question, investment professionals. The question was based on risk for two probabilities that had the exact same expected value (2700) but one offered twice the certainty while the other offered twice the return. This potentially might mean that the investment professionals are slightly riskier than other populations, but there may be an alternative explanation.

Further research by Tversky and Kahneman (1992) in advances in prospect theory developed a method of rating decisions based on a certainty equivalent. When using the same certainty equivalent formula it was found that the certainty equivalents of Q5.3 (using the same metrics for power for gains and probability weighting parameters for gains as Tversky and Kahneman (1992)) came back as option A (3000, 0.9) having a certainty equivalent of 2038.39, while option B (6000, 0.45) returned a certainty equivalent of 2089.41. This means that under the same conditions Tversky and Kahneman (1992) would expect people to favour option B, which in this case the investment professionals have, but the result is different to the original prospect theory (Kahneman & Tversky, 1979).

The other question that showed a difference in outcome was Q5.05. The investment professional population preferred option B (-3000, 0.25) over option A (-4000, 0.2). There was also a slight downgrade in preference for Q5.04 and Q5.06 even though the final results where the same.

It could be argued that the investment professionals had a different loss to gain ratio than the population of the original study, hence they took the higher probability option but with the lower loss. Determining a gain versus loss ratio can be difficult and is different across each population, the range has tended to be between 1.5 and 2.5 (Novemsky & Kahneman, 2005).

Q5.05 (A -4000, 0.2; B -3000, 0.25) has a different aspect that needs to be looked at. The difference between a 20% probability and a 25% probability is small and the population of this study may have looked at it as a negligible difference. Kahneman and Tversky (1979) described this as the simplification problem, where people tend to round probabilities to what they think of as the same. For example, 0.51 is typically rounded in an individual's mind to a 50% chance. The difference between 0.25 and 0.2 simply may have been rounded in the investment professionals mind's to a single figure, resulting in the lower outcome loss only being compared.

To build the construct first a determination of the "riskier" choice was done. To do this the certainty equivalent scores of each option were compared (Tversky & Kahneman, 1992). The score with the higher expected value but lower certainty equivalent was deemed the riskier option.

The overall construct resulted in a mean of score for the respondents of 0.38. This shows that investment community is in general risk averse, and in fact do choose the safer option in general. This is similar to the risk propensity found in the DOSPERT scale of between 44% and 49% (Weber et al., 2002).

6.5.2.1 Prospect Theory Scale Demographics

There were no statistically significant differences in the categorical means found. This means that using population as a whole was relatively homogenous. The only variable that was found to be even close to significantly different was the type of risk from a fund. At an 85% certainty level (which is too low to be significant but worth a mention) the mixed fund managers were seen to have a slightly higher mean than the managers that focused on a single risk level.

6.5.3 Comparison of Two Personal Risk Propensity Scales

The two risk propensity scales produced relatively similar results, within 3-9% of each other. Although this may be challenged as the correlation is not particularly strong (0.14) it is important to note that the two scales were testing the same thing but in very different ways.

The Risk Propensity Measurement Scale (RPMS) was designed using a descriptive method of risk propensity where the outcome of risk is based on what the individual perceives of themselves, and how they will take that action. The prospect theory scale is based on pure probabilistic outcomes that do not take into account the descriptive setting that the respondent finds themselves in.

The differences, however, do not rule out a comparison and it is relevant that the two scales resulted in a similar score to each other as well as to the more descriptive DOSPERT scale (even though it is not investment based) (Weber et al., 2002). The similar results to each other as well as to a widely used external scale make the scales comparable as constructs and in this case, add validity to the testing of the risk propensity of the investment professionals.

6.6 Hypothesis One: Underdog Bias and Self-Rated Performance

The exploration of the relationship between underdog bias and self-rated performance is based on the idea that people are often motivated by their contributions. This may lead to an improved self-image over the barriers that they have had to overcome (Ross & Sicoly, 1979). This relationship led to Davidai and Gilovich (2016) mentioning in their paper that "self-enhancement motives might aid and abet the phenomena" (p.836), resulting in what could be perceived as a tacit link between self-attribution or overconfidence in one's abilities, and underdog bias.

In this research it was proposed that not only would overcoming stiffer burdens increase your self-attribution but that because of the availability of the memories of having overcome those burdens (Tversky & Kahneman, 1973) and by not understanding what others have gone through (Pronin, Gilovich, & Ross, 2004), the level of underdog bias that is faced will be positively correlated to the self-rated performance of the individual.

Interestingly, the opposite result was found. Although there was a weak correlation, the correlation was statistically significant that the level of underdog bias in an individual will negatively predict their individual self-rated performance.

Davidai and Gilovich (2016) did leave open the potential that, in some cases, the relationship between overconfidence in one's abilities may work against underdog bias, specifically instances where people are looking forward, and where individuals are optimistic about their future. It is possible that the respondents from the study looked at their self-rated performance as part of their future self, for instances what they will be doing in the future.

This would mean that optimism bias plays an influential part in the level of self-rated performance as the respondents where rating themselves on what they think they will do instead of what they have done (Lovallo & Kahneman, 2003). It is worth investigating in future studies if this effect is specific to the investment industry. It may be possible that because of the nature of the investment industry that having to look forward and believe in your abilities is more important than other industries.

If we propose that the boundary condition for underdog bias has been fulfilled, then the personal feedback benefits received would have been highly salient in the minds of the investment professionals (reducing their underdog bias (Davidai & Gilovich, 2016)), while at the same time feedback would have stoked the ego of the investors (increasing their self-rated performance measures (Ross & Sicoly, 1979; Schroeder et al., 2016)).

The positive interpersonal interactions may be coupled with the Taleb's (2007) narrative fallacy, or hindsight bias, where the events that affected their investment decisions were not in their control and anyone would have made the same decision, faced with the same information (Fischhoff, 1975). Minimising the negative decision made in the past (even making it almost positive) (Taylor, 1991).

This means that not only would the positive feedback from the individuals and negative feedback from the market have reduced the underdog bias, it would have increased self-rated performance at the same time, resulting in the negative correlation.

While the boundary condition may have caused the negative correlation between underdog bias and self-rated performance and result in the opposite to the expected positive correlation, it is important to understand that until there is further research done on different populations the interaction between the two constructs cannot be determined as true for all populations. The result of the testing of the interaction between the constructs and the overview of the literature on the two constructs suggest that the investment industry may be the exception to the rule rather than the rule.

6.7 Hypothesis Two: Underdog Bias and Personal Risk Propensity

Davidai and Gilovich (2016) showed that individuals that feel like they are facing stronger headwinds than others will do what they believe is necessary to even the playing field, even if this means that this results in questionable behaviour from the individual.

The questionable behaviour was linked to a higher risk propensity as the individuals trying to right those wrongs were taking risks that, if caught, would result in recourse that may jeopardise their career or current place in society. This led to hypothesis two where underdog bias was positively correlated to risk propensity. What was found was that the two constructs are not linked and are independent of each other, regardless if you use the RPMS or the prospect theory scale.

This means that individuals that engage in righting their perceived wrongs do not believe that they are taking on additional risk by doing so. This outcome is significant as it questions what individuals perceive as risky behaviour. It may mean that the individuals taking the risk of righting these wrongs feel justified in what they are doing and thus believe that they are not taking on any additional risk.

This would show that risk propensity in taking on certain different behaviour is not affected when individuals do what they think is justified. Perhaps, indicating that when people are making things more “fair”, they do not believe that they are doing anything risky, they are doing what they think is right. This could create a blind spot for individuals as they do not realise the risk that they are taking. The stronger they believe in their convictions the more risk they take on (Heath & Tversky, 1991; Hoffmann et al., 2013). They believe so much in what they are doing is right that they don’t perceive the risk that they are taking on.

The perception of doing what is right will sit outside of the risk propensity measurement as the individual may not even perceive the risk. Slovic, Fischoff, Lichentsein and Roe (1981) showed that perceived risk always has some level of subjectivity. It is possible that when people think that they are righting a wrong or doing the right thing they do not feel like they are taking additional risk. They are rather restoring what is right.

The righting of wrongs may fit into the locus of control which shows that when individuals feel like they have control or at least there is the appearance of control they tend to take more risks (Gilovich & Douglas, 1986). The actual increase in taking risks may not be perceived by the risk taker as they feel that they have control over the situation, keeping their natural risk propensity similar but ignoring what is actually happening while taking the risk.

The lack of a relationship between underdog bias and risk propensity may also be due to the righting of wrong actions that are described in Davidai and Gilovich's (2016) paper are not from similar populations. The test in the original paper was done on university academics and was perhaps slightly ethically lax behaviour that would cause a problem if discovered but would result in mild repercussions. Comparatively, if an investment professional was caught doing ethical lax actions the repercussions may result in jail time. This would oddly mean that the academics are more prone to changing their risk behaviour based on the level of underdog bias they feel compared to investment professionals.

The investment professionals do not feel the same need to change their behaviour based on the headwinds they face. This could be due to the regulatory framework (and resulting punishment of potential jail time) that the investment professionals have to work in. This result would coincide with the lower underdog bias score from the investment professionals as they don't perceive their headwinds to be particularly strong or put another way they don't believe that they were benefiting any less than the others around them.

6.8 Hypothesis Three: Self-Rated Performance and Personal Risk Propensity

Self-rated performance and the overconfidence that comes from having a high degree of self-rated performance has been shown to be a factor in risk perception (Slovic et al., 1981). There have even been links between a heightened overconfidence and risk propensity through the planning fallacy (Lovallo & Kahneman, 2003). These links were the base for hypothesising that there was a positive correlation between self-rated performance and risk propensity.

When testing of the two constructs occurred, it was shown that there was no relationship between self-rated performance and risk propensity (when using either the RPMS or the prospect theory scale). This means that an individual with a high self-rated performance, or put another way someone that believes they are well ahead of their peers does not have an increased risk propensity. Therefore self-rated performance is not a good predictor of personal risk propensity. Although this is good for the more hubris of the investment community, it does have implications for the study.

Lovallo and Kahneman (2003) showed that CEOs take risks that outweigh the benefits through the planning fallacy, but the study was done on what the CEOs had done in the past. At the point in time when the CEOs were making their decisions, they may not have realised they were taking on excess risk. Kahneman (2011) used himself as an example when trying to put together a textbook on prospect theory, his team were setting themselves up for failure through overconfidence but there was little realisation that by shortening the time frames of the project they were adding additional risk to the project's completion. This could mean that the individuals could take risks that they initially thought that they would not.

King and Slovic (2014) showed that feelings get in the way of accurate risk assessments, which may lead people to not thinking that they are taking the risks that they are. Similarly, it may also lead individuals to thinking that they will not take a certain risk in the future. This may lead to people that are risk seeking due to their level of self-rated performance to think that they are unlikely to make risky decisions in the future as they have control of what they are going to do (Gilovich & Douglas, 1986). It would be interesting to compare if the (self-administered) risk propensity of the investment community are linked to what the actual risks that the investors take.

Sometimes individuals do perform take actions or do things that they themselves see as irrational or exceptionally risky. This is due to compulsive behaviour that we either don't control or where we take action in a situation based on gut feel rather than sitting back and analysing a situation. Different authors have described this phenomenon differently but two of the more common terms are implying two minds in one brain and a brain at war with itself (Evans, 2008). This phenomenon of a brain at war with itself may be the reason why we there is not a correlation between self-rated performance and risk propensity.

The investment community is however very aware of risk. Although it is difficult to quantify the term of risk, the information on index funds or unit trust refer to a level of risk. It is conceivable that because of the investment community's high level of awareness to risk in general that they are very sensitised to their actions when risk is involved. This may mean that the population as a whole have managed to separate their self-rated performance from the risk that they take on, which may be the reason why there is no relationship between self-rated performance and risk propensity.

6.9 Summary of the Discussion

The sample size of the population turned out to be relative similar to what was expected from other studies in similar populations. The study was male dominated with a high level of education.

There was a surprisingly low underdog bias score seen in the population. This may be due to the nature of the investment industry as the benefits the professionals perceive are of a human interaction type (which are more easily recalled (Taylor, 1991)), while the barriers are systematic and market related, or faced by everyone equally. These two events in combination cause the boundary condition of underdog bias to be fulfilled where people do not perceive that they face stiffer headwinds than the tail winds that support them (Davidai & Gilovich, 2016).

The alternative explanation is that the investment community in South Africa does not feel that they face stiffer headwinds or barriers than others. They didn't feel that they were significantly hampered by external factors in comparison to their peers. This is pertinent in two ways, firstly, that South African investment community may be an exception compared to other sectors of society. Secondly, and more importantly, in a South African context that has historically been divided and still suffers from societal divisions the investment community has potentially managed to find a way through those divisions.

The analysis of the demographics found that females had a statistically significantly higher underdog bias than their male colleagues. This potentially may be due to the male dominated investment industry.

The self-rated performance construct had a relatively expected result where the investment professionals felt that on average, they were better than average. This was comparable to studies done on different populations testing the better than average effect (Guenther & Alicke, 2010) and as well as the work of Williams and Gilovich (2008).

Individuals with the most experience and the least experience had statistically significant different means to the overall construct. The investors with the least experience had the lowest self-rated performance while the professionals with the most experience found that they had the highest level of self-rated performance.

The personal risk propensity construct was tested using two metrics, the Risk Measurement Propensity Scale (RPMS) and a measurement instrument based on prospect theory. The study was testing the RPMS for the first time and found that the results were in line with the likes of the DOSPERT scale (Weber et al., 2002) and the Hoffman, Post and Pennings study (2015).

The prospect theory measurement instrument had similar results to the original work of Kahneman and Tversky (1979). The two scales were then compared to each other and showed that they too had similar results. This validated the new scale as well as gave the study two different mechanisms to test the hypotheses with.

Hypothesis one had a surprise result where underdog bias was negatively correlated to self-rated performance. This was likely due to the boundary condition of underdog bias being fulfilled in the overall population. The boundary condition is unique as it only happens when the benefits an individual receive are personal (received from individuals), and the barriers they face are from uncontrollable factors or things that are explainable in the past (Davidai & Gilovich, 2016). The salience of the personal benefits received would boost an individual's self-rated performance as the personal nature of the feedback would be difficult to compare to others personal feedback (Schroeder et al., 2016; Tversky & Kahneman, 1973). This creates the situation where the underdog bias of the individual is reduced and at the same time increasing self-rated performance.

Hypothesis two showed that there was no relationship between underdog bias and personal risk propensity. This caused an interesting investigation into the action of individuals that try to make things right when they perceive that others have bigger benefits than they receive. It is likely that the actions that people do to right the "wrongs" they perceive they do not feel that they are taking on any more risk, the action that they are taking is, in fact, corrective and right, thus carrying no risk. This could potentially create a blind spot as individuals take on more risk than they realise.

Hypothesis three tested to see if there was a positive relationship between self-rated performance and personal risk propensity. It found that there was no relationship between the two constructs. There were two possible scenarios that described the outcome. Firstly, it may be possible that the investment community is so sensitised to risk (due to the nature of the industry) that the investment professionals have managed to separate risk propensity from their level of hubris.

The second option may be that the investment professionals may perceive that their risk propensity is low (as they score themselves in what they will do in the future) but their actual risk level is higher depending on the degree of confidence they have in their abilities to control the situation (Lovallo & Kahneman, 2003; Slovic et al., 1981).

7 Conclusion

7.1 Introduction

The dissertation set out to understand the relationship among the three different constructs, underdog bias, self-rated performance and risk propensity, as well as to understand the different levels of each construct that exist in the South African investment community.

The rest of the chapter will outline what the research objectives including sub-objectives followed by the results of the research. It will then continue to what the implications are for business, any additions to existing literature, the recommendations for further study, and the limitations of the study.

7.2 Recap of Research Objectives

There was one high-level key objective of the study and six sub-objectives of the study. The main objective of the research was to understand the relationship between underdog bias, self-rated performance, and personal risk propensity. This would allow businesses to understand some of the factors that influence risk propensity in investment professionals and the implications of that in the different firms.

The sub-objectives were:

a) Understand the level of underdog bias (Davidai & Gilovich, 2016) that exists within the investment community.
b) Understand the level of self-rated performance that exists within the investment community and what that level of overconfidence (Williams & Gilovich, 2008) is compared to the current average that exists in literature.
c) Understand the different levels of risk propensity that exists in the investment community using a new scale specifically developed for the research (The Risk Propensity Measurement Scale) and a risk propensity measurement scale that was based on prospect theory (Kahneman & Tversky, 1979).
    i. Test and analyse the validity of the new personal risk propensity scale
    ii. Understand the different or similar outcomes to the risk propensity outcomes from the prospect theory scale
d) Provide screening or testing recommendations to potential businesses that require the matching of risk propensity to specific job roles.

7.3 Summary of Findings

The key objective of the study was to understand the relationship among the three key constructs, underdog bias, self-rated performance and risk propensity. To test the relationships three hypotheses were developed. Before the relationships could be tested, the three constructs were developed and analysed as stand-alone constructs. Once they were understood then the relationships between them were tested.

The first construct that was tested was underdog bias (sub-objective A). The overall level of underdog bias was strangely low, below the midpoint. This indicated that the investment professionals did not think that their barriers loomed larger than their benefits, or put another way that they were grateful for getting to the positions they were in. This may have been the result of the boundary condition of underdog bias being found. If the boundary condition was fulfilled, it was a unique result as the condition had only been hypothesised until now, and would indicate a different result to what Davidai and Gilovich (2016) had come across in their studies on underdog bias. In all of their experiments they found that people tended to feel their barriers more than their benefits.

One of the important conditions that Davidai and Gilovich (2016) included in the study was the boundary condition where people tended to remember the benefits they received from people more than any other. This could outweigh the barriers if those barriers were not people orientated. The investment professional industry appears to have fulfilled this condition which caused the overall sample to have a low underdog bias score, believing that they have had more benefits than barriers. To confirm the boundary condition and its existence it will be important, in future studies, to test similar populations that exhibit similar conditions of shared barriers and individualised personal benefits. This will be explored in more detail in the recommendations for further research.

The second construct was the self-rated performance construct (sub-objective B). The construct score was similar to other studies tested using other, but similar, methods (e.g. Williams and Gilovich (2008) and Geunther and Alicke (2010)). The overall construct score showed that the investment professionals thought that on average, they were above average when compared to their peers in the investment industry.

The third construct of personal risk propensity was split into two measures. The first was the Risk Propensity Measurement Scale (RPMS) which was developed specifically for this study and a prospect theory scale which was similar to the scale used by Kahneman and Tversky (1979) in their original paper on prospect theory.

The RPMS was designed using a descriptive method to test risk propensity. Where the outcome is based on what risk level the individual indicates they will take on through their actions. This is different to other scales which are usually based in either the perception of the market risk (Hoffmann et al., 2013) or in the individual choice of potential outcomes (Tversky & Kahneman, 1992). To test the validity of the RPMS it was compared to other similar studies. The results found that the RPMS is comparable to other scales on risk (e.g. Weber, Blias and Betz (2002)).

The second scale used to measure risk propensity was similar to the work done by Kahneman and Tversky (1979) in prospect theory. Sixty percent of the questions were borrowed from the questions used in the original study. A comparison of the results showed that apart from one difference which was explained using the certainty equivalent value (Tversky & Kahneman, 1992) the results of the original study and this study were very similar.

The two risk propensity scales were then compared and were found to be different by between 3-9%, or put in more descriptive terms, the results were very similar. This finding validated the RPMS further as a measurement tool in analysis risk propensity in the investment industry (sub-objective C both (i) and (ii)).

The final sub-objective (D) of providing screening or testing recommendations to businesses that requires matching of risk propensity to specific job roles requires more testing. The initial results that have come from the RPMS have been good but to ensure that the test is viable across different industries and different populations more work needs to be done.

The first part of tackling the main objective was hypothesis one, which looked at the relationship between underdog bias and self-rated performance. The initial hypothesis was that there was a positive correlation between the two constructs. When the actual testing was done the relationship between underdog bias and self-rated performance turned out to be weakly negatively correlated. This means that if an individual of the investment community has a weak underdog bias score, they are more likely to have a high self-rated performance score. The surprising outcome may have been due to the boundary condition of underdog bias being fulfilled (Davidai & Gilovich, 2016).

The boundary condition requires that the benefits that the individual receive are personalised and are given by one person (typically a manager or senior) to another. This is different to the barriers faced which are shared and impersonal (i.e. market feedback). The benefits that are received are typically done in a private setting (or at least not public to everyone). This would mean that the individuals that are getting the positive feedback or benefits are not aware of the positive feedback that others are receiving. This creates an asymmetry of information or simply an availability bias (Tversky & Kahneman, 1973) where people may think that they get the greater share of praise than others, enhancing the perceived benefits that the individual receive, lowering the underdog bias felt. This unique condition may be the reason why underdog bias is weakly negatively correlated to self-rated performance (higher individual praise means lower underdog bias score as others don't get the same as me but feel the same barriers from the market, and higher individual praise increases the self-rated perception of performance).

Hypothesis two looked at the relationship between underdog bias and risk propensity. What was found was that there was no statistically significant relationship between underdog bias and risk propensity, using either the RPMS or prospect theory scale. This is a very interesting outcome based on what individuals understand their risk propensity to be, as there may be a space where an individual's actions are not perceived to be risky by the individual, yet in a different circumstance, they think they are unlikely to do the same action.

Hypothesis three looked at the relationship between self-rated performance and risk propensity. Similarly to the result in hypothesis two there was no statistically significant relationship between self-rated performance and risk propensity (using either scale). This is in itself is significant because it is different to what Lovallo and Kahneman (2003) found. The major differences in the studies was that Lovallo and Kahneman (2003) used the decisions that their population had already made (based in past tense) as the basis for excessive risk, in this study respondents were asked to rate their risk propensity in what they thought they were likely to do in the future. An interesting area of study may be to compare the results of the risk propensity measures with the actual results that the respondents choose.

An alternative explanation may be that the investment community has to deal with risk or what they term to be risk daily. The population may then be highly sensitised to the level of risk that they can take on which may result in the specific population managing to separate risk from self-rated performance.

7.4 Recommendations and Implications

There results of the study have been different to the original hypotheses but they have provided different insights into how the three different constructs affect individuals and more specifically how the constructs affect investment professionals.

7.4.1 Implications for Business

Both of the personal risk propensity measures showed that the risk of the overall investment industry was not above what can be found in the general population. This is good news for individuals that have their savings invested in the industry, as the overall average risk propensity of the professionals is similar to the general population.

The self-rated performance was also similar to what can be found in the general population. This debunks the stereotype of the arrogant investment professional, which is also good news for the industry. This does perhaps leave a space open for the PR of the investment firms to start to remove this stereotype, or at least break down some of the boundaries.

Interestingly investment professionals seem to suffer from underdog bias less than the rest of the general population. Taken on face value, this is a good thing, but because the boundary condition for the bias was fulfilled, it means that there may be a worry that the professionals don't often believe that the barriers they face are due to them. This may mean that they don't acknowledge their mistakes, or worse own up to them. This needs to be looked at from an HR perspective if it is true.

The lack of a relationship between underdog bias and risk propensity can be worrying for business as it shows that people that are righting the wrongs that they perceive do not seem to think that they are taking on additional risk. This may provide a blind spot for investment professionals when they are trying to fix what they perceive to be wrong. This blind spot could be costly for investors if the "wrong" that is being righted actually results in further loss.

Similarly, the lack of relationship between self-rated performance and risk propensity does not mean that the investment professionals with a high degree of self-belief (or arrogance) do not take more risks than others, Lovallo and Kahneman (2003) have shown others in similar positions do. It means that people do not think that they will take the high risk until they actually do. It can be compared to how individuals believe that they are going to eat healthy until they are given the choice of a cheeseburger. The difference in perception and actual action needs to be carefully monitored by firms.

To mitigate this risk, there are pseudo indicators that have shown to increase the accuracy of self-assessment, which will decrease the likelihood of an elevated self-rated performance. Individuals with a high locus of control, individuals that score high on cognitive complexity measures, and strangely individuals that identify as introverts on the Myers-Briggs Type Indicator are all more likely to have more accurate self-assessments (Yammarino & Atwater, 1993)

The Risk Propensity Measurement Scale (although further testing needs to be done) proved valuable in understanding and individual's risk propensity. It may be useful for investment companies to align their investment professionals to funds that follow a similar risk profile to the professionals. This would allow individual investors or clients to get the maximised value from their investment professional as the professional is operating in his or her natural risk level. Matching is particularly important as investors have difficulty learning from their experiences and often fail to update their behaviour to match those experiences (Hoffmann et al., 2013).

7.4.2 Theoretical Implications and Recommendations for Further Research

The underdog bias construct may have fulfilled the boundary condition. This requires further examination as it is possibly an anomaly. If it is found in similar populations (any group that is in an industry where the success is based on outside factors, an example would be farmers, fisherman or potentially scientists) then the boundary condition should be studied further to truly understand the factors that derive it. If the boundary condition is found and can be recreated in different populations it will open up an interesting dynamic where industries create environments that cause gratitude to be saliently felt more than barriers in those individuals. This could (idealistically) create a framework to give insights into how to create happier workplaces for people.

The Risk Propensity Measurement Scale showed promising results in the testing of risk propensity when compared to the prospect theory scale as well as other similar measurement tools. To fully confirm the scale as reliable more testing needs to be done on other populations as well as on the same population to create norms for different samples.

Further research needs to go into risk propensity and the self-regulation of risk propensity. There is a worry that individuals answer what they expect they will do and not what they actually will do when faced with the same option. Stephens-Davidowitz (2014) warns that individuals (even in anonymous surveys) tend to answer in the way that they think they should act and not in how they actually do act. This leads to an implicit bias where we think one thing of ourselves but in fact do another. The risk propensity measure needs to be confirmed by using scenarios that are likely to occur and then compared to what the subjects do when actually faced with the same problems.

7.5 Limitations of the Study

The study found some interesting results which have resulted in unexpected discussion points. The research may (although it has tried not to) have fallen victim to the narrative fallacy by explaining the unexpected results instead of assuming that the results are just potentially outliers and may not be repeatable (Taleb, 2007).

The Risk Propensity Measurement Scale was developed specifically for this study. There has been an attempt to validate the scale by comparing the results to the prospect theory scale other similar scales in different studies. But the scale has not been tested in different environments and different populations. The researcher acknowledges that the scale requires more research to be fully validated.

The results were taken from a population that is highly educated and at the same time conscious of what the research was attempting to study. In this way, it is conceivable the results that were given were designed to present the respondents in their best possible light (even though they knew it was anonymous) (Stephens-Davidowitz, 2014). This may have reduced the effectiveness of the results gathered.

The population is a very specific set of individuals that operate exclusively in the South African investment environment. While this helped with the homogeneity of the study, it means that the results may not be useful to the general population.

7.6 Conclusion

The study showed that the linkages between some constructs, although they seem clear are not always what they appear to be from the literature. Underdog bias as a construct is still new and has not been studied in the same level of detail that the other two constructs have. By potentially finding the boundary condition the study has opened up a new exciting avenue for research that may allow the conditions of the working environment to create a more grateful and hopefully happier workplace.

The development of the RPMS has been useful and with further research may aid other researches in getting a better understanding of risk propensity in different populations.

The indication that there is a blind spot that may hamper an individual’s perceptions of themselves is worth investigating further and was a particularly interesting result of the research.

The three hypotheses all came back with different than expected results. This has helped build a better understanding of the different constructs even if they were found to be different to the expected results. The different results have opened up new avenues for research that may hopefully lead to a better understanding of how different feedback affects risk propensity and how people rate themselves.

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9 Appendix 1

9.1 Online Survey

As part of my MBA I am conducting research on different variables that can help to determine the levels of risk that exist in the investment community. To assist with the research please can you assist me by filling out the following survey.

The survey should take no longer than 20 minutes of your time.

Participation in the survey is voluntary, you may leave at any time without any penalty. All data will be kept confidential. By completing the survey you are indicating that you are a voluntarily participating in this research. The survey is designed to ensure anonymity and confidentiality.

The paper will be completed by the end of March 2018. If you would like the final report I will be happy to send it to, or if you have any concerns you are welcome to contact me.

Thank you for your participation in the survey

Regards

Sean Combrink

sean@combrink.com or 082 440 9701

Section One:

Please state your age: (18-29/30-39/40-49/50-59/60+)

What is your gender? (Male/Female)

How many years have you been in the investment industry?:(0-5/6-10/11-15/16-20/21-25/26+)

What is your highest level of education? (High school or lower/ diploma/ bachelor's degree/ post graduate diploma/ honours/ masters/ doctorate)

What level of risk is the fund typically targeted at? (Conservative/Moderate/High)

Section Two:

For each of the following statements please indicate the level it normally applies to you.

Please select an answer on the following 7 point Likert scale: (Entirely Agree/ Mostly Agree/ Somewhat Agree/ Neither Agree or Disagree/ Somewhat Disagree/ Mostly Disagree/ Entirely Disagree)

Question 2.1:

When I source research, I have to work harder than others to achieve the same result.

Question 2.2:

I don’t know why but I seem to have more difficulty than others securing meetings with key directors.

Question 2.3:

I find it easier to communicate with investors than others.

Question 2.4:

My investors are more demanding than other investors, even when I produce the same results.

Question 2.5:

My investment committee is convinced more easily to invest in my proposals than others.

Question 2.6:

I have to work harder than others to get the recognition I deserve.

Question 2.7:

My investors tend to blame me more harshly than others when the market takes a downturn.

Question 2.8:

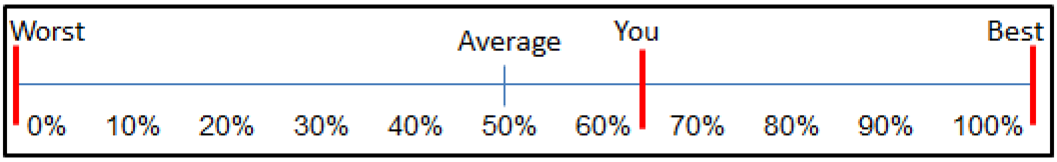
My peers get more recognition than they deserve compared to the work that they have done.

Section Three:

Please answer the following questions in relation to where your perceive yourself to be when compared to your peers.

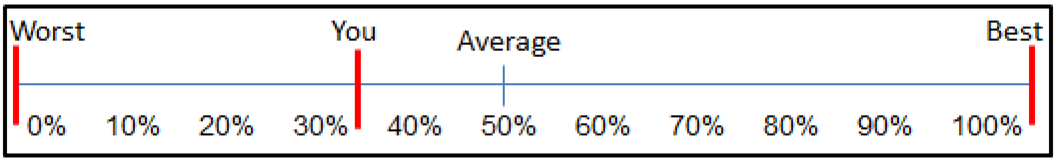
For example: Where do you rate in terms of sprinting at your local running club?

Top: *66%* *Slightly above average*



Where do you rate in terms of weight lifting at your local gym?

Top: *32%* *Below average*



Question 3.1:

I am confident I get the success I deserve at work

Top:

Question 3.2:

Sometimes I get depressed with the investment industry *(reversed)*

Top:

Question 3.3:

I generally generate returns above my targets.

Top:

Question 3.4:

Sometimes when I fail, I feel like I can’t choose the right investments *(reversed)*.

Top: ☐

Question 3.5:

I complete my tasks successfully.

Top: ☐

Question 3.6:

Sometimes I do not feel in control of my portfolios *(reversed).*

Top: ☐

Question 3.7:

Overall I am satisfied with my performance.

Top: ☐

Question 3.8:

I am filled with doubts about my competence *(reversed).*

Top: ☐

Question 3.9:

I determine what will happen in the investments we make.

Top: ☐

Question 3.10:

I do not feel in control of my success in my career *(reversed).*

Top: ☐

Question 3.11:

I am coping with most of the problems at work.

Top:

Question 3.12:

There are times when things look pretty bleak and hopeless in the investment industry *(reversed).*

Top:

Section Four

For each of the following statements please indicate the level it normally applies to you.

Please select an answer on the following 7 point Likert scale: (Entirely Agree/ Mostly Agree/ Somewhat Agree/ Neither Agree or Disagree/ Somewhat Disagree/ Mostly Disagree/ Entirely Disagree)

Question 4.1

I take more risk than my fellow investors

Question 4.2

I have worried about investment decisions I've taken knowing they are overly risky

Question 4.3

My investment decisions are rational and are very unlikely to harm the fund *(reversed)*

Question 4.4

I get a thrill by taking decisions that I don't know the outcome of

Question 4.5

I have been scolded for taking risky decisions *(reversed)*

Question 4.6

If I could take a little bit more risk I could secure a higher return for my fund

Question 4.7

The more risk I take the better I perform

Question 4.8

Before I make any investment I do more of a thorough analysis than others *(reversed)*

Question 4.9

I like to take risks

Question 4.10

I tend to take large but reasonable risk in my investment decisions

Section Five

In this section please answer the question as to which option you would prefer either A or B

For the following questions please assume you administer a fund or investment portfolio of R10 million

Question 5.1

A: 80% chance of R4 million and a 20% chance of nothing

or

B: 100% chance of R3 million

Question 5.2

A: 20% chance of R4 million and a 80% chance of nothing

or

B: 25% chance of R3 million and a 75% chance of nothing

Question 5.3

A: 45% chance of R6 million and a 55% chance of nothing

or

B: 90% chance of R3 million and a 10% chance of nothing

Question 5.4

A: 80% chance of losing R4 million and a 20% chance of nothing

or

B: 100% chance of losing R3 million

Question 5.5

A: 20% chance of losing R4 million and an 80% chance of losing nothing

or

B: 25% chance of losing R3 million and a 75% chance of losing nothing

Question 5.6

A: 45% chance of losing R6 million and a 55% chance of losing nothing

or

B: 90% chance of losing R3 million and a 10% chance of losing nothing

Question 5.7

A: 50% chance of losing R2 million and a 50% chance of gaining R4 million

or

B: 60% chance of losing R3 million and a 40% chance of gaining R6 million

Question 5.8

A: 30% chance of losing R3 million and a 70% chance of gaining R2 million

or

B: 50% chance of losing R3 million and a 50% chance of gaining R5 million

Question 5.9

A: 80% chance of losing R1 million and a 20% chance of gaining R5 million

or

B: 30% chance of losing R2 million and a 70% chance of gaining R1 million

Question 5.10

A: 30% chance of gaining R2 million and a 70% chance of losing R1 million

or

B: 20% chance of gaining R4 million and an 80% chance of losing R1.5 million

9.2 Consistency Matrix

The relationship among underdog bias, self-rated performance and personal risk propensity

Hypotheses	**Literature Review**	**Data Collection Tool**	**Analysis**
Hypothesis One: There is a positive correlation between underdog bias and self-rated performance	Davidai & Gilovich, 2016; Tversky & Kahneman 1973; Kahneman & Lovallo, 1993, 2003; Ross & Sicoly, 1979; Agans & Shaffer, 1994; Fischhoff, 1975; Guenther & Alicke, 2010	Question section two and three in questionnaire	Each question will be given an equal weighting and formed into an individual construct, those constructs will be used in regression analysis to understand the correlation of the variables
Hypothesis Three: There is a positive correlation between self-rated performance and personal risk propensity.	Kahneman & Lovallo, 1993, 2003; Ross & Sicoly, 1979; Agans & Shaffer, 1994; Fischhoff, 1975; Guenther & Alicke, 2010 Kahneman & Tversky, 1979 Novemsky & Kahneman, 2005	Question sections three, four and five in the questionnaire	
Hypothesis Two: There is a positive correlation between underdog bias and personal risk propensity	Davidai & Gilovich, 2016; Kahneman & Tversky, 1979 Kahneman & Tversky, 1979; Novemsky & Kahneman, 2005	Question sections two, four and five in the questionnaire	

10 Appendix 2 – Ethical Clearance

Gordon Institute of Business Science
University of Pretoria

14 September 2017

Sean Combrink

Dear Sean,

Please be advised that your application for Ethical Clearance has been approved.

You are therefore allowed to continue collecting your data.

We wish you everything of the best for the rest of the project.

Kind Regards

GIBS MBA Research Ethical Clearance Committee