UNIVERSITY OF KWAZULU-NATAL

THE IMPACT OF DEMOGRAPHIC FACTORS ON SUBJECTIVE FINANCIAL RISK TOLERANCE: A SOUTH AFRICAN STUDY

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A thesis submitted in fulfilment of the requirements for the degree of Master of Commerce (Finance)

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2011

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ACKNOWLEDGEMENTS

I would like to express my sincere appreciation and gratitude to my supervisor, Mr Barry Strydom, for his unwavering guidance and assistance in producing this thesis. His continual encouragement and support, as well as patience, helped in keeping me committed and motivated. His valuable advice, throughout the process, benefited me considerably and his efforts were greatly appreciated.

The immeasurable support and encouragement from my parents and the special one in my life ensured that I persevered no matter what. Their deep love and support will always be appreciated and, without them, this never would have been possible. I would also like to thank the Lord for blessing me with the ability and the opportunity to complete my thesis. The support from close friends and family was greatly appreciated as well.

LIST OF ACRONYMS

AHEAD	– Asset and Health Dynamics Among the Oldest Old
ANOVA	– Analysis of Variance
AP	– Arrow-Pratt absolute risk aversion coefficient
CARA	– Constant absolute risk aversion
CFA	– Chartered Financial Analyst
CRRA	– Constant relative risk aversion
DARA	– Decreasing absolute risk aversion
DC	– Defined-contribution
DRRA	– Decreasing relative risk aversion
HRS	– Health and Retirement Study
IARA	– Increasing absolute risk aversion
IRRA	– Increasing relative risk aversion
IRS	– Internal Revenue Service
MPT	– Modern Portfolio Theory
odv	– Ordered dependent variable method of analysis
OLS	– Ordinary Least Squares
ROE	– Return-on-equity
RRA	– Relative risk aversion
RRAI	– Relative Risk Aversion Index
SARS	– South African Revenue Services
SCF	– Survey of Consumer Finances
SPSS	– Statistical Package for the Social Sciences
SSS	– Zuckerman Sensation-Seeking Scale Survey
UKZN	– University of KwaZulu-Natal
US	– United States

ABSTRACT

Financial risk tolerance, an investor's appetite for financial risk, is an extremely important aspect that needs to be considered when constructing investment portfolios. Evidence as to how risk tolerance should be measured is mixed, with each method having its own strengths and weaknesses. It can be determined both objectively and subjectively, depending on the method used, and can be influenced by a variety of demographic characteristics. Debate as to how certain demographic factors influence risk tolerance is widespread, providing support for further study in this field, particularly from a South African perspective.

The purpose of this study was to investigate to what extent demographic factors influenced an individual's willingness to take on levels of financial risk. The study used an existing, but adapted, subjective questionnaire to determine the risk tolerance levels of a sample of respondents. Respondents were categorised at an aggregate level as either being below or above average risk tolerant. A Binary Logistic model was used to analyse the effect of the independent demographic variables on risk tolerance and it was found that age and gender were significantly related to risk tolerance, whilst there was mixed evidence as to the relationship between risk tolerance and race as well as income. The findings from the study provide new evidence from a wider South African sample and could be used by financial advisors to improve their understanding of risk tolerance and its demographic determinants, as well as companies wishing to align their employees' risk profiles with the overall company risk profile, as examples.

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1 INTRODUCTION

An increasingly important decision-making process an individual faces today is how to most effectively determine the asset allocation of his/her investment portfolio. The significance of this decision is often underestimated given its impact on the financial well-being and retirement plans of people. In its broadest term the asset allocation process involves investing portions of one's money/wealth into cash (money market), bonds or stocks. However, the various markets in which one can invest are characterised by different levels of risk, both in contrast to one another as well as within each market. The cash or money market is considered to be relatively risk free compared to the stock market which is deemed to be more risky. Within the bond market an investor could pursue a riskless strategy by investing in Treasury Bills or Government bonds or, alternatively, in lower grade or junk bonds if he/she sought a high risk investment. The proportional allocations by investors are generally based on the person's appetite or tolerance for risk where, in its simplest form, an investor could be considered either risk averse or risk tolerant (to a certain degree). The importance of financial risk tolerance in an investor's asset allocation decision is highlighted by Hanna and Lindamood (2004: 27), Sung and Hanna (1996: 11) and Subedar, McCrae and Gerace (2006: 2) amongst others.

1.1 Background to the Study

Every individual is characterised by their own unique risk tolerance level and one's threshold for taking on more risk is constantly tested in everyday matters. However, when individuals are faced with financial decisions their risk tolerance is a key determinant on how they act, or do not act for that matter. Due to this, the investment and financial services industry is heavily reliant on the correct assessment and measurement of financial risk tolerance. Hanna, Gutter and Fan (2001: 53) define risk tolerance as a measurement of an individual's willingness, or ability, to take on risk and this is similar to Hallahan, Faff and McKenzie (2004: 57) who view it as an "…attitude towards accepting risk". Markowitz's Modern Portfolio Theory (MPT) uses an investor's utility function for risk and return to determine the optimal portfolio with this being represented by the asset combination that maximises the investor's utility (Yook and Everett, 2003: 48). The use of this expected utility method involves the trade-off between risk and return, with lower risk levels being associated with lower returns and *vice versa* (Hanna and Lindamood, 2004: 27). Inherent in this relationship is the fact that an investor's risk aversion or alternatively, risk tolerance, is an important factor in deciding on optimal portfolio allocations (Hanna and Lindamood, 2004: 27).

Hanna and Chen (1997: 17) and Subedar *et al* (2006: 2) highlight the importance of financial advisors being able to measure an investor's risk tolerance correctly and most effectively as this forms a vital part of their investment strategy. This point is extremely relevant as all financial advisors are required to comply with the "know your client" rule when in the process of advising an individual (van Wyk, 2008: 18; Subedar *et al*, 2006: 3). Recognising an investor's risk tolerance level is widely regarded as being an important part of advising clients on appropriate financial products, however, the ability to actually, and accurately, measure these levels is very rare (Hanna and Lindamood, 2004: 29). Hallahan *et al* (2004: 59) and Hanna *et al* (2001: 53) noted that the use of subjective questionnaire techniques have been used as the primary measure to determine risk tolerance amongst investors to date. Sung and Hanna (1996: 11) stated that a key consideration when determining optimal portfolio allocations is that of risk tolerance. Accordingly, it was suggested that the results from their study would have important implications for financial advisors and planners alike, particularly when consulting with and advising clients (Sung and Hanna, 1996: 11).

An interesting study about the risk tolerance perceptions that financial advisors form for individual investors was conducted by Riley and Russon (1995: 66). According to Riley and Russon (1995: 65) effective asset allocation is affected by two inputs which are expected capital market returns and the investor's appetite for, or ability to, tolerate risk. They further stated that there has been little research which helps one to understand what affects risk tolerance but coverage on expected capital market returns has been exhaustive. Riley and Russon (1995: 65) highlight the importance of asset allocation and the impact risk tolerance levels can have on this by mentioning two problems that financial advisors or money managers face when dealing with allocation decisions. The first problem is that there may be a very poor allocation of funds by the advisor and therefore, the investor may not have adequate funds at a certain future date or it could result in a loss in wealth for the investor. Secondly, based on the first problem a money manager may be held responsible for the poor performance and risk losing his or her job (Riley and Russon, 1995: 65). In their study the two authors aim to provide an explanation of individual financial risk tolerance in such a way that it addresses both of the aforementioned problems.

The study by Riley and Russon (1995: 66) used a quantitative model that included features of psychological and economic paradigms and hypothesized that individual risk tolerance was a function of factors such as time horizon, salary, expected salary growth, age, gender, marital status and number of children (Riley and Russon, 1995: 66). A survey sent to Chartered Financial Analysts (CFA) required them to determine an appropriate risk tolerance level for different client scenarios and then indicate their choice of asset allocation between United States (US) bonds, US equities and/or cash equivalents. Using the responses from the CFA advisors, an implied perceived risk for each client scenario was calculated (Riley and Russon, 1995: 66).

The study suggested that the implied risk tolerance of a client was dependent on two sets of factors. The first group of factors consisted of the investor's time horizon, salary, client age and salary growth, and was referred to as the structural component, whilst in the second it was related to gender, marital status and the number of children in the household (Riley and Russon, 1995: 67). The findings from the study concluded that the risk tolerance perceptions of the advisors were significant for time horizon, salary level, marital status, number of children and gender (Riley and Russon, 1995: 68-69). Furthermore, the perceived level of risk tolerance for females was greater than that of males which counters the general belief that females were less risk tolerant as found by authors such as Pålsson (1996: 785), Hartog, Ferrer-i-Carbonell and Jonker (2000: 11), Hallahan *et al* (2004: 67) and Al-Ajmi (2008: 21-22).

The study by Riley and Russon (1995: 68-69) shows that financial advisors base their risk tolerance judgements according to perception or heuristics and that this could lead to misclassification errors which are very problematic. Furthermore, it is evident that there is debate as to how certain factors affect and, how they are perceived to affect, individual risk tolerance levels and underlines the importance of accurately assessing each and every individual investor in order to match the advice and investment products to their risk profile. Subedar *et al* (2006: 2) mentioned that there is a probability that financial advisors can misclassify investor's risk preferences as the investors themselves are not often always aware of their own tolerances. To negate this problem it was stressed that advisors needed to collect reliable and relevant information from investors, rather than rely on heuristics, which identifies the investor's investment goals and their financial risk attitudes (Subedar *et al*, 2006: 2). The biggest disadvantage, according to Subedar *et al* (2006: 3), of using heuristics to classify investors in terms of risk was that they did "...not provide the financial advisor with any directly observable measure of an investor's attitude to situations that characterise financial investment decisions (choice under uncertainty)."

The above discussion highlights the importance of financial advisors conducting accurate risk tolerance assessments in order to avoid the potential problem of misclassification. Over and above this the lack of consensus on how certain demographic factors affect individual risk tolerance provides important support for further research into these relationships as is the purpose of this study. However, it must be noted that the use of a risk tolerance measure is not only limited to a financial advisory role as it could potentially be used as an important assessment tool of employees by employers. This would be particularly relevant in the financial and banking sector amongst portfolio and fund managers. A company who wishes to employ a fund manager would not want to employ someone who is very risk averse as this could lead to a very conservative investment strategy, possibly conflicting with the company's overall risk policy, and as such lower returns, possibly below the market index or competitor funds. As a result the company could lose clients and the fund, or even worse the entire company, is shut down. Therefore, such a tool could be tailor made to identify those potential managers who are characterised by the appropriate risk tolerance the company desires.

This need not only apply to portfolio and fund managers as most, if not all, companies are faced with investment and acquisition decisions as well as the evaluation of new projects at some point in time. Considering this, it is vital that the managers entrusted with this decision making responsibility are representative of the company's desired risk profile and measuring an employee's risk tolerance level, possibly as part of a psychometric test procedure, would help achieve this. Sung and Hanna (1996: 11) also stated that risk tolerance could also play an important role in influencing governmental financial policies and decisions.

A study, in the petroleum industry, by Walls and Dyer (1996: 1006), found that in an industry which is perceived to be characterised by high levels of risk, managers were in fact found to make decisions which may be viewed as risk averse and a firm's performance was impacted on by "corporate risk-taking behaviour" (Walls and Dyer, 1996: 1020). It can, therefore, be seen that the applications of a risk assessment tool are not limited to a pure financial advisory role and can potentially be used just as effectively in monitoring a company's risk policy or determining an employee's or manager's risk tolerance level. However, just as an individual can be characterised with a certain risk tolerance level, there are certain social and demographic factors which are believed to mould a person into a risk category somewhere on the scale between highly risk averse and risk tolerant. Studies as to how certain demographic factors affect one's appetite for risk are quite widespread internationally, however, locally in South Africa it has received relatively little focus and offers an ideal opportunity for further research.

1.2 Research Problem and Objectives of the Study

To date the literature on this topic has been limited in the South African context. Two studies that have looked at the issue were those of Strydom, Christison and Gokul (2009) and Gumede (2009). These studies were, however, limited with regards to the sample size, the scope of the demographic variables investigated and, particularly in the case of the Strydom *et al* (2009) paper, the method of analysis. Therefore, the research problem is to determine to what extent demographic factors influence an individual's willingness to take on levels of financial risk from a South African perspective. The study uses a measure of subjective risk tolerance administered to a more representative sample and employs the use of a more robust form of statistical analysis.

The specific research objectives of the study are:

- To determine whether age affects individual subjective risk tolerance
- To determine whether there is any difference in individual subjective risk tolerance levels for males and females

- To determine whether education level affects individual subjective risk tolerance levels
- To determine whether marital status has any effect on individual subjective risk tolerance levels
- To determine whether race affects individual subjective risk tolerance levels
- To determine whether income affects an individual's subjective risk tolerance level
- To determine whether religion affects individual subjective risk tolerance levels

1.3 Scope and Method of Analysis

The purpose of the study is to examine the relationship between an individual's subjective risk tolerance levels and certain demographic factors. Whilst relevant, the concept of objective risk tolerance is outside the scope of this study. The point of the study is not to develop an appropriate instrument to measure subjective risk tolerance, rather the existing Grable and Lytton (1999a) instrument, adapted to the South African context will be used. Adaptations will be made by using more familiar South African financial terms as opposed to the US terminology in the original questionnaire. This instrument has previously been rigorously tested for both reliability and validity and the results support its use. The author aims to improve on the Strydom *et al* (2009) and Gumede (2009) studies, which used student samples, by administering a questionnaire to a more heterogeneous and larger sample and including more demographic factors in the analysis. The mall intercept survey technique will be used but the study sample will be limited to a sample of respondents from the Pietermaritzburg area. The ramifications of this are that the sample cannot be construed as being representative of the entire South African population, however, the results will allow for important inferences to be made.

Various statistical procedures are to be applied to the data in order to examine the various relationships and to test the research hypotheses. Non-parametric techniques are to be used to conduct median analyses, similar to the Strydom *et al* (2009) study allowing for a direct comparison of the results. Furthermore, a Binary Logistic regression will be performed on the data allowing for hypothesis testing to be conducted based on the results from the full multivariate model, from which important conclusions can be drawn. The results could potentially provide further support for the notion that individual financial risk tolerance is influenced by a person's demographic characteristics.

1.4 Outline of the Study

The research paper is structured as such; the following chapter serves as an introduction to the theoretical framework upon which risk aversion and risk tolerance were defined. Chapter three reviews the previous research on the relationships between certain demographic variables and financial risk tolerance. Chapter four provides a detailed description of the methodology to be used in the paper whilst, in chapter five, the data analysis and findings are discussed. Finally, chapter six concludes the study.

2 RISK TOLERANCE: A THEORETICAL FRAMEWORK

Financial risk tolerance, an investor's appetite for financial risk, can be measured both objectively and subjectively. Objective measures typically assess an individual's risk tolerance through revealed behaviour (MacCrimmon and Wehrung, 1985: 2), whilst subjective measures generally assess an individual's "self-perceived risk tolerance" level (Chang, DeVaney and Chiremba, 2004: 54). Traditional Economic theory has favoured using the measures, both objectively and subjectively, for risk aversion developed by Arrow and Pratt in the determination of individual risk preferences. MacCrimmon and Wehrung (1985: 2) stated that this was because in Economics researchers have generally avoided asking individuals direct questions. However, there have been an increasing number of studies in the Finance field which have shifted to using other subjective forms of determining risk preferences, such as questionnaires, in measuring risk tolerance, which is said to be the inverse of risk aversion. The following chapter details the foundations of the Arrow-Pratt framework, its applications and limitations and also defines risk tolerance in relation to risk aversion and introduces the various alternatives that are used to measure it.

2.1 The Von Neumann-Morgenstern Utility Function and the Foundation of the Arrow-Pratt Framework

Economic theory linked to risk attitudes has traditionally been based on the assumption that individuals make decisions in order to maximise their expected utility, "...where utility is a function of the outcome variables and heuristics of the probability distributions" (Ferrer, 1999: 29). Yang (2004: 23) stated that, the foremost theory used to model consumer decisions involving risk was the expected utility approach developed by von Neumann and Morgenstern and that the central notion was that rational consumers would select a choice with the highest expected value. According to Eaton, Eaton and Allen (2005: 580), if an individual prefers one option to another then the preferred option has a higher expected value or utility. If the individual was indifferent between the two options then they have the same expected utility (Eaton *et al*, 2005: 580). Furthermore, Levy and Levy (2002: 265) commented that Economic and Financial models have generally assumed a non-decreasing utility function with diminishing marginal utility. The diminishing marginal utility principle, according to Levy and Levy (2002: 265), was the cornerstone to the development of the von Neumann-Morgenstern expected utility theory used in most Economic models. Support for the widespread use of the von Neumann-Morgenstern expected utility theory was given by Hauser and Urban (1979: 251-252) who believed that it was unique and useful because it could model risk explicitly in its axiomatic foundations.

Hauser and Urban (1979: 252) explained that the theory bases the choice of a utility function on an individual decision maker's response when faced with a risky option or a riskless option. According to Ferrer (1999: 30), using expected utility theory, risk aversion can be defined in terms of the concavity or convexity of an individual's utility function at any chosen point. Whilst Yang (2004: 23), commented that an individual's risk preference can be modelled using one of three expected utility functions. According to Yang (2004: 23), an expected utility function of this nature can be shown, in mathematical notation, as follows:

$$U(x, p) = Sp_iU(x_i) \qquad (2\text{-}1)$$

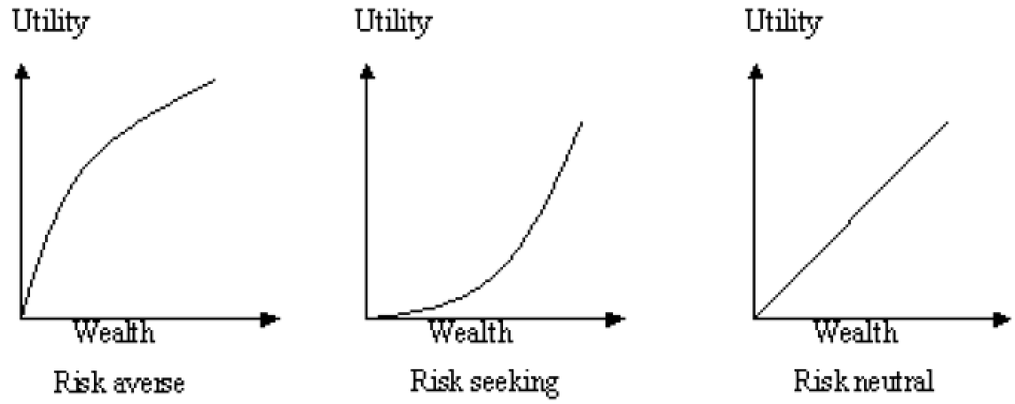
Where: U = the utility derived from an outcome of a lottery (denoted x);

p = the probability of the outcome (x) occurring; and,

Sp_i = the sum of all the probabilities = 1.

Following from this, a risk averse individual is characterised by $U(Sx_ip_i) > Sp_iU(x_i)$ and is represented by a concave utility function (Hauser and Urban, 1979: 252 and Yang, 2004: 23). A risk loving or seeking individual is represented by a convex utility function and $U(Sx_ip_i) < Sp_iU(x_i)$ (Hauser and Urban, 1979: 252 and Yang, 2004: 23). An individual who is indifferent between two choices (i.e. risk neutral) has $U(Sx_ip_i) = Sp_iU(x_i)$, which is represented by a linear utility function (Hauser and Urban, 1979: 252 and Yang, 2004: 23). The following figure shows these utility functions:

Figure 2-1: Expected Utility Functions



Source: Yang (2004: 23)

Some problems associated with the expected utility theory were, however, noted by Yang (2004: 23-24). Firstly, the assumption that an individual acts rationally when facing risk is not always the case and is referred to as the Allais Paradox (Yang, 2004: 23). Secondly, expected utility theory also assumes an individual's risk preferences are consistent and will not change these preferences when presented with different scenarios or problems (Yang, 2004: 24). This has, according to Yang (2004: 24), led to some researchers developing improved measures such as those by Kahneman and Tversky (1979) and Friedman and Savage (1948), however, the expected utility theory has provided the foundation for these developments. The expected utility theory was also used in the work by Arrow (1971) and Pratt (1964) in their models of risk aversion.

The foundations of Arrow and Pratt's definitions for absolute risk aversion, relative risk aversion and decreasing absolute risk aversion are related to concave utility functions and these conjectures have since become vitally important in Economic theory (Kihlstrom, Romer and Williams, 1981: 911 and Levy and Levy, 2002: 265). Levy and Levy (2002: 265) acknowledged their importance even further by stating that "...risk aversion is a key assumption in most economic and finance equilibrium models, which break down once the risk aversion assumption is violated."

The Arrow-Pratt measures of risk aversion are explained in more detail below.

2.2 The Arrow-Pratt Concept of Risk Aversion

Arrow (1971) and Pratt (1964) developed the concept of measuring risk aversion as a concave utility function denoted as U over wealth which is denoted W (Halek and Eisenhauer, 2001: 2). According to Babcock, Choi and Feinerman (1993: 18) the probability premium was used to derive the measures in Arrow's work in contrast to Pratt (1964: 124) who used the risk premium in his development. Pålsson (1996: 773) reasons that risk aversion is a measure of an inability or unwillingness to accept risk, whilst Menezes and Hanson (1970: 482) define risk aversion in the Arrow-Pratt framework as follows: "[a]n individual is a risk averter if for any arbitrary risk he prefers the sure amount equal to the expected value of the risk to the risk itself." This is confirmed by Protopopescu (2007: 2) who adds that "[t]raditionally, risk-aversion is equivalent to the concavity of the utility function (viewed as the measure upon which the agent bases his decisions)."

There are two components to the Arrow-Pratt measure for risk aversion, being that of absolute risk aversion and relative risk aversion. Cohn, Lewellen, Lease and Schlarbaum (1975: 605) note that these measures were independently developed by Arrow and Pratt but they serve as a way to determine the "…amount and proportion of wealth placed by an investor into a risky asset when his portfolio decision is limited to choosing combinations of a riskless asset and that one risky asset." Levy (1994: 289) states that the measures of absolute and relative risk aversion are vital in understanding investor behaviour and theoretical issues in Economics and Finance, and provided examples illustrating why this is so. One such example is if investors are characterised by constant relative risk aversion then one can use the "utility function of the form which allows myopic decision in the multiperiod investment decision" (Levy, 1994: 289). A more detailed discussion of the Arrow-Pratt absolute and relative risk aversion measures follows.

2.2.1 Absolute Risk Aversion

More specifically, absolute risk aversion is defined as the change in a nominal amount that is allocated to a risky asset as wealth increases and is represented by the following function (Arrow, 1971 and Pratt, 1964):

Absolute Risk Aversion (R_A) = -U"(W)/U'(W) (2-2)

Where: U" = Concave utility function differentiated twice;

U' = Concave utility function differentiated once; and,

W = Wealth.

This function was said to be a suitable measure of the local absolute risk aversion of an individual who maximises the expected value of the (twice differentiable) von Neumann-Morgenstern utility function U (Kihlstrom *et al*, 1981: 911). Levy and Levy (2002: 265) stated that the expected utility theory developed by von Neumann and Morgenstern is used as the framework in a large number of fundamental models used in Economics and Finance with the Arrow-Pratt risk aversion models being no different. The authors mentioned that the models used to define absolute risk aversion, relative risk aversion and decreasing absolute risk aversion in the Arrow-Pratt contextual framework were related to the concavity of utility functions. The reason for the concave utility function being instrumental in the formation of such Economic models is that it implies convex indifference curves, a falling marginal rate of substitution and non-specialisation (Levy and Levy, 2002: 265). Furthermore, Levy and Levy (2002: 265) highlight that risk aversion is an important assumption in these equilibrium models and the violation of this causes these models to fall apart.

By taking the derivative of R_A with respect to Wealth (W) one can then determine whether an individual is characterised by decreasing absolute risk aversion (DARA), constant absolute risk aversion (CARA) or increasing absolute risk aversion (IARA) when the derivative is either less than zero, equal to zero or greater than zero respectively (Levy, 1994: 290). This is shown mathematically as follows:

1. If $\partial R_A/\partial W < 0$ then DARA applies;
2. If $\partial R_A/\partial W = 0$ then CARA applies; and,
3. If $\partial R_A/\partial W > 0$ then IARA applies. (Levy, 1994: 290)

2.2.2 Relative Risk Aversion

Conversely, relative risk aversion is referred to as the change in an individual's portfolio allocation as their wealth base increases (Arrow, 1971 and Pratt, 1964). The mathematical formula for Pratt's relative risk aversion measure is shown below, with the same definitions of U", U' and W above, applying.

Relative Risk Aversion (R_R) = $-W[U''(W)/U'(W)]$ (2-3)

In a similar fashion to that shown above (for DARA, CARA and IARA) the derivative can be used to define decreasing relative risk aversion (DRRA), constant relative risk aversion (CRRA) and increasing relative risk aversion (IRRA). The mathematical notation for each is shown as such:

1. If $\partial R_r/\partial W < 0$ then DRRA applies;
2. If $\partial R_A/\partial W = 0$ then CRRA applies; and,
3. If $\partial R_A/\partial W > 0$ then IRRA applies. (Levy, 1994: 290)

Siegel and Hoban (1982: 481) discussed these results and suggested that DRRA arises when a higher proportion of wealth is invested in risky assets as wealth increases (less risk averse behaviour) conversely, IRRA exists when the proportion of wealth allocated to assets classified as more risky decreases as wealth increases. Intuitively, CRRA is exhibited when the allocated amount does not change as wealth increases.

2.2.3 Partial Risk Aversion

Menezes and Hanson (1970: 481) developed an interesting additional measure which they call partial relative risk aversion. It is noted that the absolute measure of risk aversion for an individual is important when wealth varies, whilst when wealth and the risk are varied in the same proportion the relative measure is more appropriate. The partial relative risk aversion measure is said to be applicable when the risk is varied and wealth is held constant or is fixed. Menezes and Hanson (1970: 481) use the following function to define their partial measure, where U(T) represents a utility function for wealth:

Partial Relative Risk Aversion (R_P) = -TU"(T + W)/U'(T + W) (2-4)

Through their mathematical proof the authors reiterated that:

> "The behavior of the absolute risk aversion A gives information about the behavior of the risk premium when wealth is varied but the risk is fixed; the behavior of the relative risk aversion R gives information about the behavior of the proportional change in the risk premium when wealth and the risk are changed in the same proportion; and finally, the behaviour of partial relative risk aversion P gives information about the behaviour of the proportional change in the risk premium resulting from a given proportional change in the risk, wealth remaining fixed" (Menezes and Hanson, 1970: 485).

Although, it is possible for DARA, CARA or IARA to exist in terms of absolute risk aversion and DRRA, CRRA and IRRA in terms of relative, the hypotheses of DARA and IRRA were initially formulated by Arrow (Menezes and Hanson, 1970: 485). In the case of DARA, Menezes and Hanson (1970: 485) comment that such a result is reasonable as it suggests an individual will buy less insurance as wealth increases for a given risk level. With respect to IRRA it implies that wealth allocated towards insurance spend increases when wealth and risk increase in the same proportion. Menezes and Hanson (1970: 485) further explained that an IRRA scenario entails that "…the elasticity of the risk premium with respect to the multiplicative factor by which both wealth and the risk are increased is greater than unity…"

Bajtelsmit, Bernasek and Jianakoplos (1999: 3) noted that generally it has been concluded that the absolute measure of risk aversion decreases with wealth, which results in a higher amount being invested in risky assets as an investor's wealth increases. However, the findings with regards to relative risk aversion are not as conclusive and it is said that the differences could be attributed to other factors such as age and income (Bajtelsmit *et al*, 1999: 3).

Menezes and Hanson (1970: 485) postulated, that if an individual possesses an initial positive level of wealth and the partial relative risk aversion is monotone, then R_P is strictly increasing in T, alternatively the individual is characterised as risk-neutral.

However, Menezes and Hanson (1970: 485) claimed that if one accepts Arrow's IRRA hypothesis, then R_P is strictly increasing and based on their theory the hypothesis of increasing partial relative risk aversion is supported.

2.2.4 Application of the Arrow-Pratt Coefficient of Relative Risk Aversion

The following application illustrates how the Arrow-Pratt coefficient of relative risk aversion is used in a study to determine risk appetites. The example is taken from Schooley and Worden (1996: 88) and shows how the ratio of risky assets to wealth for an investor can be used to determine their risk aversion level using the Arrow-Pratt framework.

The first step in estimating relative risk aversion is to maximise an investor's utility function using a Taylor series expansion (Schooley and Worden, 1996: 88-89). Following that, the risky asset proportion (α) of an investor's portfolio can be written as:

$$\alpha = [E(r_m - r_f)/\sigma^2(r_m)] * [1/(1-t)(1-h)C] - h/(1-h) * \beta_{h,\,m} \qquad (2\text{-}5)$$

Where: r_m is the return on the market portfolio of all risky assets;

r_f is the return on the risk-free asset;

t is the investor's tax rate;

h is the ratio of investor's human capital to his total wealth;

$\beta_{h,\,m}$ is the ratio of the covariance of r_m and r_h (the return on human capital) to σ_m^2; and,

C is Pratt's measure of relative risk aversion (RRA).

(Schooley and Worden, 1996: 88-89)

Beta is said to be close to zero as it is estimated from time-series data, therefore, equation 2-5 becomes:

$$\alpha = [E(r_m - r_f)/\sigma^2(r_m)] * [1/(1-t)(1-h)C] \qquad (2\text{-}6)$$

which can be rewritten as:

$$(1 - t)(1 - h)\alpha = MPR*1/C \qquad (2\text{-}7)$$

Where: MPR is the market price of risk, assumed constant across all households.

(Schooley and Worden, 1996: 88-89)

Therefore, $(1 - t)(1 - h)\alpha$ is proportional to C (i.e. RRA) and can be observed, conclusions about RRA can be made from $(1 - t)(1 - h)\alpha$. For example, if for an investor, $(1 - t)(1 - h)\alpha$ increases (decreases) when wealth increases, they are said to show decreasing (increasing) RRA (Schooley and Worden, 1996: 88-89).

2.2.5 Limitations of the Arrow-Pratt Measure

The Arrow-Pratt measures of risk aversion, their applications and variations have received extensive coverage in previous literature, however, there do exist some drawbacks to using the measures and these need to be accounted for before any meaningful analysis can be conducted. Two of these limitations are that the scale and the range of the data affect the measures (Ferrer, 1999: 31) and because of this the Arrow-Pratt measures need to be adjusted for these two factors (Ferrer, 1999: 31 and 37). Ferrer in fact devotes, in his discussion on the Arrow-Pratt measures, a considerable proportion to the explanation on the impact of scale and range (Ferrer, 1999: 30-44).

According to Ferrer (1999: 31) the effect scale and range have on Arrow-Pratt measures is probably best explained by the work of Pratt (1964). In his initial workings, Pratt (1964: 125) uses the risk premium, the variance of the risky prospect and r(x) to illustrate that the relationship shown below exists:

$$\prod(x, Y) = 0.5\sigma^2_Y r(x) + o(\sigma^2_Y) \qquad (2\text{-}8)$$

Where: $\prod(x, Y)$ is the risk premium given a level of wealth x and a risky prospect Y;

σ^2_Y is the variance of the risky prospect;

r(x) is the Arrow-Pratt measure at a level of wealth x; and,

$o(\sigma^2_Y)$ are the higher order terms in the Taylor series expansion of the expected utility function around a mean of x.

(Pratt, 1964: 125; McCarl and Bessler, 1989: 57 and Ferrer, 1999: 31)

Rearranging equation 2-8 to solve for r(x) yields:

$$r(x) = 2[\prod(x, Y) - o(\sigma^2_Y)]/\sigma^2_Y \tag{2-9}$$

McCarl and Bessler (1989: 57) and Ferrer (1999: 31-32) refer to Tsiang (1972), who claimed that if the dispersion of the risk prospect is assumed small relative to wealth, then the term $o(\sigma^2_Y)/\ \sigma^2_Y$ can be ignored. Therefore, r(x) is shown, approximately, as follows:

$$r(x) \approx 2\prod(x, Y)/\sigma^2_Y \tag{2-10}$$

Subsequently, Ferrer (1999: 32) commented that from the equations showing the exact and approximate expressions of r(x) (equations 2-9 and 2-10) it is obvious that it is dependent on x (wealth) and Y (the risk situation or level). Due to this it is claimed that the Arrow-Pratt measure "…has associated with it a unit, the reciprocal of the unit with which Y is measured since the certainty equivalent is divided by the variance of Y. Because σ^2_Y and not E[Y] affects r(x), the magnitude of AP [Arrow-Pratt absolute risk aversion coefficient] is not affected by the use of incremental rather than absolute terms, or *vice versa*. Furthermore, it is apparent that a change in σ^2_Y will affect r(x). For example, a mean preserving increase in risk, i.e. σ^2_Y increases whilst x and the expected value of Y remain constant, will decrease r(x)" (Ferrer, 1999: 32).

Babcock *et al* (1993: 20), Ferrer (1999: 33), McCarl and Bessler (1989: 61) and Raskin and Cochran (1986: 205) all include tables of some variation to illustrate, according to Ferrer (1999: 33), "the inconsistencies in magnitudes of elicited [Arrow-Pratt] values [in previous studies]". In the study conducted by Ferrer (1999: 34) it was noted that, from the literature examined, the Arrow-Pratt values exhibited, ranged from 12.17 in one study to 0.000000921 in another, furthermore, in some studies the values are expressed to five decimal places, whilst in others it is seven or nine. In Raskin and Cochran's (1986: 204) study, the upper bounds on Arrow-Pratt measures deemed to be almost risk neutral ranged from 0.000001 to 0.005, whilst the authors also concluded that from their table it was evident that most coefficients were assumed, based on certainty equivalents or on secondary data from other studies. Compounding this was the fact that there were major inconsistencies between the coefficients or classifications of specific coefficient values (Raskin and Cochran, 1986: 204).

An illustration of how important an impact scale can have on the data was also covered by Raskin and Cochran (1986: 206). In converting Arrow-Pratt measures into marginal utility values, it was shown that for values of 0.0002 and 0.0003, which are relatively close, the difference in the marginal utility of the 10 001st dollar would be three times whilst for the value of the 50 001st dollar it would be 160 times. McCarl and Bessler (1989: 56) and Ferrer (1999: 34) state that it was surprising how many studies have assumed Arrow-Pratt values or used values from previous studies, without adjusting for the scale and range of the data used in the original study (Ferrer, 1999: 34). McCarl and Bessler (1989: 56) claimed that "[s]uch a procedure is questionable since individual characteristics influencing utility functions, the dispersion of the risky prospect, and wealth levels would change between studies." It was, however, highlighted by Ferrer (1999: 34) that proving the inaccurate use of Arrow-Pratt measures was impossible in most studies because the information supplied on the stochastic income distributions, from which the Arrow-Pratt values were drawn, was inadequate.

The issue of scale and range is not only limited to studies in the Agricultural Economics field and has been evidenced in Economic and Finance studies as well. Hanna *et al* (2001: 54) discussed limitations of using the Arrow-Pratt measure, in an objective sense, which have been linked to the fact that estimates of the coefficient of RRA have varied greatly depending on the data used, assumptions made and the estimation methods. Hanna *et al* (2001: 54) cited the study by Pålsson (1996), who used cross-sectional data on portfolio allocation, as an example. In the study by Pålsson (1996: 786), the Arrow-Pratt coefficients of RRA were estimated to be between two and four when housing was excluded as a type of financial asset. However, when housing was included, the coefficients were much higher and ranged from ten to 15. This shows that depending on the definition used, both the range and scale of the coefficients can change.

A further limitation in using Arrow-Pratt measures is linked to the fact that an individual's wealth needs to be determined. Levy (1994: 303) states that in order to extrapolate more accurate data one would be required to analyse the behaviour of investors at various points in their economic life-cycle and, most notably, when the investor's wealth level changes. Due to this it was said that testing DARA and IRRA empirically is extremely difficult and possibly unattainable. In their study on RRA, Siegel and Hoban (1982: 485), found mixed results in terms of IRRA, CARA and DRRA when altering their definition of wealth. The authors claimed that if wealth was defined narrowly, RRA increased for poor households, whilst it decreased for wealthier households. They attribute the behaviour of the poorer households possibly due to the reason that their repaying of debt dominates their acquisition of risk assets. However, if housing was included in the definition of wealth, then both poor and wealthy households exhibited IRRA behaviour. Similarly, when net worth and nonmarketable assets were included in the definition, IRRA with respect to wealth occurred (Siegel and Hoban, 1982: 485).

Based on the evidence presented above one can see that the particular measure of wealth used does potentially lead to differing results. In order to overcome this in a study conducted by Eisenhauer (2010: 294), the author developed, using a gamble scenario, a discrete measure for risk aversion and its inverse, risk tolerance, which can be determined without "knowing the magnitude of the initial endowment wealth". The expressions, in mathematical notation, for risk aversion and risk tolerance are as follows:

$$\text{Risk aversion } (R) = g(pg - \lambda)/\, \lambda(g - \lambda) \tag{2-11}$$

$$\text{Risk tolerance } (T) = \lambda(g - \lambda)/\, g(pg - \lambda) \tag{2-12}$$

Where: p is the probability of winning the lottery in the gamble;

g is the gross payout; and,

λ is the reservation price an individual is willing to pay.

(Eisenhauer, 2010: 292-294)

From the formulae it can be seen that the level of wealth of an investor does not need to be accounted for in this case and therefore, it could be argued that it is a more suitable method of measuring risk aversion and tolerance compared to those measures where the level of wealth is required as an input.

An interesting study conducted by Siegel and Hoban (1991: 27) shows how one can break down the Arrow-Pratt measure into component ratios similar to the decomposition of the return-on-equity (ROE) ratio in the DuPont analysis. It is noted that RRA, in the Arrow-Pratt framework, is measured as a proportion of the risky assets held in a wealth portfolio, called the risk-asset ratio. This risk-asset ratio can, similar to ROE, be decomposed into its constituencies which are portfolio allocation, financial leverage and wealth accumulation. Wealth, and more importantly the definition of wealth, has already been shown to have an effect on risk tolerance (or aversion). Siegel and Hoban (1991: 27) reiterated this point by stating that previous empirical studies have used many definitions of wealth in determining the risk-asset ratio and therefore, findings on how wealth impacts risk aversion was mixed. By showing the decomposition of the risk-asset ratio the authors illustrated why the differing wealth definitions had an effect. Several studies [e.g. Cohn *et al* (1975); Friend and Blume (1975); Siegel and Hoban (1982); Morin and Suarez (1983) and Bellante and Saba (1986)] were referred to in the work by Siegel and Hoban (1991: 27-28), where wealth definitions have changed and it was shown how the conclusions drawn in the studies differed.

In the development of their model using the Arrow-Pratt RRA measure, the market price of risk, the after-tax adjustment factor and the ratio of risk assets to net worth, Siegel and Hoban (1991: 29) show that the following relationship exists:

$$\frac{\text{Risk Assets}}{\text{Total Resources}} = \frac{\text{Risk Assets}}{\text{Total Assets}} * \frac{\text{Total Assets}}{\text{Net Worth}} * \frac{\text{Net Worth}}{\text{Total Resources}} \qquad (2\text{-}13)$$

The commentary on the preceding relationship is taken from Siegel and Hoban (1991: 29-30). The ratio of risk assets to total assets, which is known as the portfolio allocation ratio, is said to be the risk-asset ratio when wealth is defined as total assets. This means that if liabilities, human capital and diversification motives are ignored a higher allocation ratio suggests a lower RRA coefficient. The second ratio, the financial leverage ratio, measured by total assets to net worth, is also one of the components in the ROE DuPont decomposition. The use of debt financing suggests a degree of risk tolerance, whilst the decreasing of debt levels may substitute for an increase in marketable assets where both reduce risk. Finally, the ratio of net worth to total resources which is also known as the wealth accumulation ratio, is said to be dependent on the factor age, where among individuals of a similar age it can be used as a measure of risk aversion. It was described that, "[a]s one converts human capital into cash flow over a lifetime, he or she chooses either present consumption or accumulation of net worth. Human capital is largely undiversified and is subject to loss through injury or illness, obsolescence of skills, errors in judgement, or economic malaise. The risk averse accumulate assets that will hedge against a loss of human capital, while those tolerant or ignorant of risk consume their wealth and accumulate fewer assets in either risky or riskless form" (Siegel and Hoban, 1991: 29-30).

Some additional limitations of using the Arrow-Pratt framework in assessing objective risk tolerance, by calculating the ratio of risky assets to wealth, are discussed further in comparing the merits of objective risk tolerance measures and subjective risk tolerance measures in section 2.4. The Arrow-Pratt framework also places heavy emphasis on measuring risk aversion, however, this study was concerned with the concept of financial risk tolerance. Risk tolerance and its link with risk aversion is explained and outlined below.

2.3 Risk Tolerance Defined

Hallahan *et al* (2004: 57) defined personal financial risk tolerance as an indication of "...a person's attitude towards accepting risk..." It was also further stated that risk tolerance influenced the asset allocation decision of investors (Hallahan *et al*, 2004: 57). Hanna *et al* (2001: 54) described risk tolerance as the opposite of risk aversion and as such that there was an inverse relationship between the two. More formally stated an increase in risk aversion resulted in a decrease in risk tolerance. This was confirmed by Faff, Mulino and Chai (2008: 2) who claimed that "individuals who are more (less) risk averse will have a lower (higher) tolerance for financial risk" and that the Economist's concept of risk aversion is inversely related to financial risk tolerance. Faff *et al* (2008: 1) mentioned that financial risk tolerance represents an individual's attitude towards risk whilst Grable (2000: 625) defined financial risk tolerance as the "maximum amount of uncertainty that someone is willing to accept when making a financial decision…"

The study by Faff *et al* (2008: 3) is extremely important in this regard as it is one of very few papers which actually investigated whether in fact there was a correlation between the two measures of risk aversion and financial risk tolerance in a practical experiment. In order to do this, participants in their study were required to undergo a two stage risk level assessment. In the first stage the individuals were assigned a risk tolerance score after completing a full psychometrically based financial risk tolerance survey. Whilst in the second stage, risk aversion was examined through the playing of lottery choice games modelled on a 2002 study completed by Holt and Laury (Faff *et al*, 2008: 3).

When comparing their study to similar previous studies, Faff *et al* (2008: 3) mentioned that five key elements were apparent. Firstly and possibly most importantly, was that the study provided insight into whether the financial risk tolerance and the risk aversion approaches were compatible. The second element was that the authors introduced higher stakes and also included more participants in the lottery games. Thirdly, the study included some rounds which had negative, or loss, outcomes allowing for conclusions on loss aversion and prospect theory to be drawn. Furthermore, the sample employed was deemed to be more representative as it was not limited to the use of students and finally, the lottery choice experiment was implemented online. Given the five key elements identified, the significance of the study was further enhanced based on the core finding that "…an FRT [financial risk tolerance] score obtained from a psychometrically validated survey and the RA [risk aversion] type of information deduced from lottery choice experiments are indeed strongly correlated" (Faff *et al*, 2008: 3 and 21).

From the literature examined above it is clearly evident that risk aversion and risk tolerance are strongly connected and there is support for the inverse relationship between the two concepts or measures. Financial risk tolerance, however, can either be measured subjectively or objectively depending on the particular method used. The contrast between the two is discussed next.

2.4 Objective and Subjective Risk Tolerance

The key determinant of objective and subjective financial risk tolerance is the framework used to measure risk tolerance. As has already been mentioned, objective measures determine risk preferences by examining revealed behaviour (MacCrimmon and Wehrung, 1985: 2), whilst subjective measures generally assess an individual's "self-perceived risk tolerance" level (Chang *et al*, 2004: 54). Hanna and Chen (1997: 17) were of the view that "...subjective risk tolerance [is] based on the economic concept of risk aversion..." and that objective risk tolerance was "...based on Malkiel's idea of the objective financial situation of the household." Chaulk, Johnson and Bulcroft (2003: 258) and Hanna *et al* (2001: 54) described that when measuring risk tolerance one could use Economic theory, employing the concept of risk aversion (the opposite of risk tolerance), which was discussed in more detail in the section detailing the Arrow-Pratt measure. Using the Economic framework, risk aversion can be measured by determining the ratio of risky assets to wealth and it is thus, an objective measure (Chaulk *et al*, 2003: 258 and Chang *et al*, 2004: 54). However, according to (MacCrimmon and Wehrung, 1985: 1), the Arrow-Pratt measure can also be used to measure subjective risk tolerance, where choices among gambles are used to determine an individual's utility function from which, "...a measure of risk propensity is derived..." This was the method used by Hanna and Lindamood (2004: 29) who measured the relative risk aversion of respondents by asking income based gamble questions similar to Barsky, Juster, Kimball and Shapiro (1997).

Perceptions and judgements were also said to influence financial risk tolerance and it was for this reason that it has also been considered as a subjective construct (Chaulk *et al*, 2003: 259). It was further stated by Chaulk *et al* (2003: 259) that "...financial risk tolerance ... [is] a psychological component of decision making under financial uncertainty, a situation in which individuals evaluate the desirability of possible outcomes and their likelihood of occurring." A study by Hanna and Chen (1997: 17) conducted expected utility analyses of portfolios in order to explain the distinction between objective and subjective risk tolerance. One of the conclusions from the study confirmed that the ratio between risky assets and total wealth was an important input for determining objective risk tolerance (Hanna and Chen, 1997: 23). The other significant conclusion pertained to subjective risk tolerance, where it was deduced that answers to hypothetical questions were related to this measure (Hanna and Chen, 1997: 23). Interestingly, it was also further suggested by Hanna and Chen (1997: 23) that the subjective risk tolerance of an investor could remain constant with age, whereas, objective risk tolerance may exhibit a positive relationship with age.

Supporting the use of a subjective risk tolerance measure, Anbar and Eker (2010: 505) claimed that an investor's risk tolerance level will change over time and was therefore, not static, especially as demographic and economic factors are altered (the factor could therefore, also change rendering the Arrow-Pratt framework redundant in such a case). Due to this, it is necessary for investment managers and financial advisors to continuously update their clients' risk profiles. However, Riley and Chow (1992: 32) provided support for the use of an objective measure due to the fact that investors' actual asset allocations were often far different from how they said they would allocate them. Riley and Chow (1992: 32) further commented that this led to the objective approach being far superior to requesting investors to respond to hypothetical scenarios. It could also be argued that the objective approach to measuring risk tolerance avoids the problem of framing when it comes to asking hypothetical questions. Halek and Eisenhauer (2001: 3), who measured risk aversion in their study objectively, noted that the framing of questions either in terms of gains or losses matters and can affect individual responses. Both objective and subjective measures have their advantages, however, there are certain drawbacks to using the methods as well.

In comparing the merits of using an objective versus a subjective measure of risk tolerance, in their study, Chaulk *et al* (2003: 259) explained that an objective measure would result in some respondents being excluded from their analysis. Their reasoning for this was that younger people and families in their formation years were less likely to have accumulated significant levels of wealth or hold risky assets. Contrastingly, most respondents would have formed attitudes towards financial risk regardless of the financial situation (Chaulk *et al*, 2003: 259). Hanna *et al* (2001: 55) and Hanna and Chen (2001: 55) inferred that Economic models may not be entirely accurate as well, due to the fact that a large number of households have very low levels of liquid assets and in turn this means they cannot hold high levels of risky assets.

Grable and Lytton (1999a: 164), in discussing the alternative risk tolerance measures, extended it to include choice dilemmas, utility analysis, objective functions, heuristic judgements and subjective assessment. In their discussion the authors acknowledged that objective measures are commonly used but the deduction of a person's risk tolerance from their asset holdings could pose serious validity concerns (Grable and Lytton, 1999a: 165). The reason for this was that objective measures were based on the assumptions that investors behaved rationally and that an individual's asset allocation was a personal choice as opposed to advice from a financial advisor. It was further stated that objective measures tended to be descriptive rather than predictive, did not account for the different dimensions of risk and generally cannot explain actual investor behaviour (Grable and Lytton, 1999a: 165).

These sentiments were echoed by Yang (2004: 21) who indicated that using asset allocations to objectively measure risk tolerance can be inaccurate as they may not necessarily be a true reflection of an individual's risk appetite. Yang (2004: 21) reasons that people may be forced into certain investments they would not usually pursue such as in the case of a company requiring employees to invest some of their pension in the company's stock or bonds which may be high in risk. In addition it was acknowledged that some individuals may experience financial constrains and are, therefore, unable to invest similar to the notion put forward by Hanna *et al* (2001: 55). Another issue raised by Yang (2004: 21) was that, in using the ratio of risky assets to wealth, definitions of risky assets are not always consistent and can result in different assessments. A final concern raised by Yang (2004: 22) was the difficulty and time consuming nature of trying to source detailed individual financial profiles in order to measure the required ratio of risky assets to wealth.

The shortfalls common to other measures, such as the objective measure, suggest that the more appropriate and accurate way to determine individual financial risk tolerance was to use a subjective measure that has been specifically designed to take into account various financial scenarios and situations (Grable and Lytton, 1999a: 165). The questionnaire method or technique, forming part of a survey, was recommended as the most preferred way of assessing individual risk tolerance partly because it allowed for a large number of respondents eliminating response bias. Secondly, the questionnaire instrument can include items that cover a wide array of financial and investment decisions or scenarios that are important in determining a risk level for an individual (Grable and Lytton, 1999a: 166).

Barsky *et al* (1997: 538) provided further support for the survey technique because "[t]he econometrician typically needs to posit a functional form. Instrumental variables are needed to control for potential endogeneity." Barsky *et al* (1997: 538) stated that using surveys overcomes these issues as one can construct a survey instrument "...that is designed precisely to elicit the parameter of interest while asking the respondent to control for differences in economic circumstances that confound estimation." More simply put, it allows for a comparison to be made on fairer terms between all respondents regardless of differences in income, for example. The survey technique is not without its own weaknesses though, as Barsky *et al* (1997: 538) acknowledged, particularly in that respondents may not be entirely accurate when answering questions. Subjective measures are, however, not limited solely to the questionnaire technique. Hanna *et al* (2001: 53) reported that there are a minimum of four methods of assessing risk tolerance which included "asking about investment choices, asking a combination of investment and subjective questions, assessing actual behaviour, and asking hypothetical questions with carefully specified scenarios." The assessment of actual investment behaviour could be construed as examining the ratio of risky assets to wealth for an investor and should therefore, be ignored as a subjective variant, whilst the others could all be deemed subjective measures.

Faff *et al* (2008: 2) were of the opinion that there are three methods typically used for measuring financial risk tolerance and these are the observation of actual investment behaviour, assessing choices in an experimental setting and creating scores from survey questionnaires. In their study Faff *et al* (2008: 3) used two methods to determine levels of subjective risk tolerance, a full psychometrically validated financial risk tolerance survey and a lottery choice game with both hypothetical and real payoffs. Another study which also used the lottery method in determining risk appetites was that done by Donkers, Mellenburg and Van Soest (2001: 165).

The above discussion shows how the concepts of risk aversion and risk tolerance have evolved and developed over time. The various ways used to measure either concept are not without their inherent strengths and weaknesses and therefore, one needs to decide on a method based on the appropriateness of that chosen method. One obviously needs to take into account factors such as time, cost and feasibility in order to make this decision. As will be detailed in the methodology chapter, the questionnaire approach in order to measure respondent's financial risk tolerance levels was used in this study.

The use of a subjective measure of risk tolerance does incorporate the possibility of characteristic traits, attributed to certain demographic factors, having an impact on an individual's risk tolerance or aversion level. The evidence as to which demographic factors, and how exactly, they affect risk taking was mixed when comparing various sources, however, the review of such literature, both internationally and South African based, provided for an interesting discussion which follows.

3 THE RELATIONSHIP BETWEEN RISK TOLERANCE AND DEMOGRAPHIC FACTORS

3.1 Introduction

It is important to note that studies pertaining to risk preference levels are not limited to the fields of Economic and Finance. The concept of risk aversion has received wide coverage particularly in the Agricultural Economics literature where authors have favoured the Arrow-Pratt framework discussed in the previous chapter. The studies by Ferrer (1999), who investigated the relationship between risk preference and soil conservation decisions, and Kisaka-Lwayo, Darroch and Ferrer (2005) who studied risk attitudes of smallholder crop farmers and the implications of these attitudes, are two South African studies which have used the Arrow-Pratt measure. There have also been numerous international studies that have used the Arrow-Pratt concept in their methodology and these include Binswanger (1980), Feder (1980), Just and Zilberman (1983), Antle (1987) and Chavas and Holt (1996). The emphasis in this study was, however, placed on financial risk tolerance, therefore, it is acknowledged that other studies on risk tolerance have been completed but are not as relevant for the purposes of this study. Studies in the Economics and Finance fields have tended to use a variety of different methods, both objective and subjective (the difference of which has already been discussed in chapter two), in measuring or assessing individual risk tolerance. Whilst some studies have followed the Arrow-Pratt framework, there have been other studies which have preferred other available methods, such as questionnaires. The following review of literature covers a wide range of Economics and Finance studies and discusses their methodologies and results in more detail.

3.2 Demographic Variables

Al-Ajmi (2008: 15) highlighted the role of risk in determining levels of return for investors and that most economic decisions, including preferences for risk, were based on individual utility functions. Therefore, understanding the determinants of risk attitudes is critical in understanding an individual's investment decision making processes. Previous studies relating to risk tolerance levels have identified a number of different demographic variables, such as race, religion and income that potentially affect an individual's desire or appetite for risk. The literature reviewed often shows conflicting results with some studies finding positive relationships between the level of risk tolerance and a variable, whilst others find a negative or no relationship for that specific variable. The demographic factors are examined further below with the international evidence discussed first followed by the two South African studies reviewed.

3.2.1 International Studies

3.2.1.1 Age

It is noted that according to logic, one would expect that as people get older risk aversion increases, as they are confronted with a shorter investment horizon in which to receive a return on their investments. Al-Ajmi (2008: 18) explained that this was reasonable as younger investors can replace leisure time with more work, decreasing their current consumption, and therefore, compensate for any portfolio losses. Over and above this, younger individuals also have a greater period of time (potentially) to recover any losses in investments. The author does, however, acknowledge that there is both evidence for and against the logical stance, furthermore, some studies find that no significant relationship exists at all.

Friend and Blume (1975: 900), in their study on the demand for risky assets by households, provided the early foundations on which later studies have based their investigations. In their study, the authors investigated the asset holdings of households in order to determine the nature of their utility functions (Friend and Blume, 1975: 900). The assumption of IRRA, covered in the previous chapter, was challenged by Friend and Blume (1975: 901) as they believed this was open to debate. The findings from the research suggested that the assumption of CRRA was generally more accurate as a description of the market place whilst they found that when wealth was more narrowly defined there was in fact an argument for the assumption of DRRA (Friend and Blume, 1975: 919).

Employing a variant of the Arrow-Pratt RRA measure, Friend and Blume (1975: 903) used a sample of cross-sectional data to determine how the coefficient varied with net worth. The data used in the analysis was sourced from the 1962 and 1963 Federal Reserve Board Surveys of the Financial Characteristics of Consumers and Changes in Family Finances. The surveys included information on households' asset and liability holdings at the end of the two years as well as the amounts and sources of income. The data gathered was then used to construct three different balance sheets which showed the ratios of household assets and other selected items to net worth (Friend and Blume, 1975: 906). Although, the authors did not explicitly investigate the relationship between age and risk aversion they did introduce a dummy variable in their regression to account for age and it was found that the coefficient on the logarithm of net worth did not change much (Friend and Blume, 1975: 910-911).

Morin and Suarez (1983: 1210) conducted a study in Canada, using data gathered from the 1970 Survey of Consumer Finances (SCF), on the demand for assets by individual households. In this particular study the authors used the Arrow-Pratt RRA coefficient and the market price of risk to determine the optimal proportion of a household's net worth which was invested in the market portfolio of risky assets, defined as the ratio of risky assets to net worth. Risky assets included stock, bonds, mutual funds, real estate not owner occupied, equity held in own business and loans held (Morin and Suarez, 1983: 1202-3 and 1205). In order to accurately analyse the effect age had on risk tolerance, a variable measuring wealth, defined as net worth or the difference between total assets and total debt, was included.

In total 8 138 households, whose wealth ranged from \$1 to \$100 000, were divided into 17 wealth or net worth groups and five age groups, furthermore, another 194 households with wealth exceeding \$100 000 were treated separately for analysis purposes and to allow for a comparison with the similar study conducted by Friend and Blume (1975) (Morin and Suarez, 1983: 1205-6). According to Morin and Suarez (1983: 1210), their results showed that, from the slope coefficients calculated in their analysis, risk aversion increased consistently with age. It was noted that although wealth was an important variable in determining risk aversion levels, life-cycles, or age, also played an extremely important role. Morin and Suarez (1983: 1213) concluded that age had an even more significant impact for households whose wealth fell between \$12 500 and \$100 000 and therefore, added that both wealth and age affect the demand for risky assets.

The life-cycle hypothesis [i.e. risk tolerance (aversion) decreases (increases) with age] was also investigated by Schooley and Worden (1996: 88) who, like Morin and Suarez (1983), also used the Friend and Blume (1975) model as a guideline. More specifically, Schooley and Worden (1996: 87) investigated the hypothesis that "…relative risk aversion (RRA) calculated from the composition of a household's portfolio and RRA reported by the household in terms of willingness to take financial risk are directly related and can be used interchangeably to proxy risk aversion." Over and above this the authors investigated the hypothesis that RRA calculated from a household's portfolio was linked to factors such as wealth, income, full-time employment, race, gender, stage of life cycle, attitude towards risk taking, desire to leave an estate and economic expectations and the adequacy of Social Security and pension income for maintaining a standard of living after retirement (Schooley and Worden, 1996: 88).

The survey was, according to Schooley and Worden (1996: 90), "...distinguished from other household surveys..." due to the considerable amount of information collected, the sample design and the treatment of non-responses. The authors mentioned that there was great disparity or income inequality between households in the US with a large proportion of wealth being held by only a relatively small proportion of households. Therefore, in order to account for the skewed wealth distribution the 1989 SCF used a dual-frame sampling technique. In total there were 3 143 households included in the sample with 2 277 randomly selected from across the US and the remaining 866 households selected from an Internal Revenue Service (IRS) developed list. Those households included from the IRS list were regarded as being high income households. Importantly, the authors acknowledged that the use of the dual-frame sample technique rendered the sample unusable as a representation of the US population, however, statistical inferences can be made as to the relationships between the variables investigated and risk aversion (Schooley and Worden, 1996: 90). The final sample used in the study excluded households which exceeded a wealth level of $1 million so as to make the results more generalisable and comparable to other similar studies. Subsequently, 2 239 households who had a positive wealth level equal to or less than $1 million were examined (Schooley and Worden, 1996: 91).

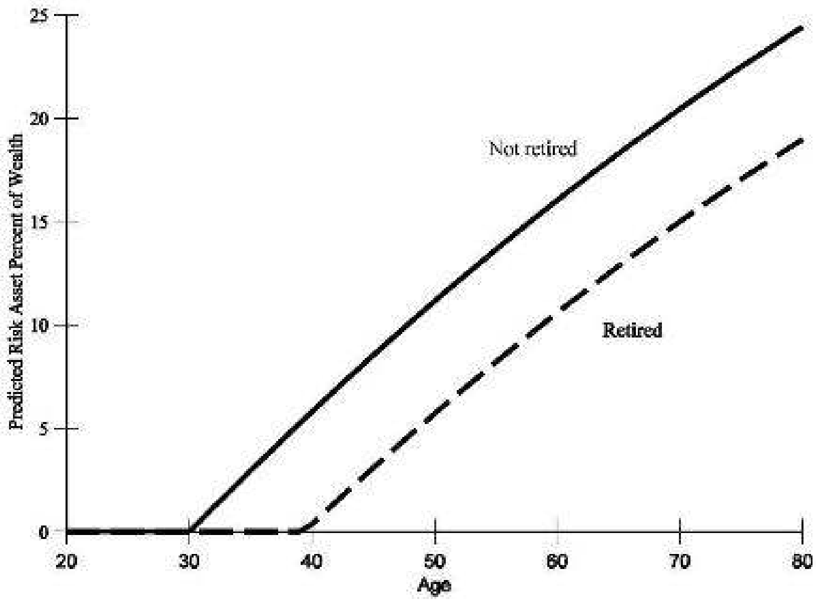
After conducting a univariate analysis on the data, Schooley and Worden (1996: 92) found that households whose heads were retired held, on average, risky assets worth less than half the value per dollar of wealth of other households. The households which consisted of young families or couples in their family formation years recorded the highest value of risky assets per dollar of wealth. Risky assets being defined in this context as "…the market value of all real estate held for investment purposes, the market value of mutual funds, corporate stock, and precious metals, the face value of all corporate and government bonds, amounts accumulated in all other pension accounts, loans to individuals, and an estimate of human capital" (Schooley and Worden, 1996: 90). The overall findings therefore, concluded that because older households held portfolios with less risky assets than those in their family formation years, risk aversion rises with age, consistent with the life-cycle hypothesis (Schooley and Worden, 1996: 92).

Another study that found evidence in support of the life-cycle hypothesis was that of Hallahan *et al* (2004: 75). Using a sample of 20 415 observations from the Australian ProQuest database, the authors concluded that there was in fact a positive relationship between age and risk aversion (Hallahan *et al*, 2004: 75). Subedar *et al* (2006: 7) explained that this result seems plausible as one would think older investors are less likely to be able to sustain losses as opposed to younger investors who still have the capacity to earn a consistent salary until retirement. Jianakoplos and Bernasek (2006: 984) was another study that used the Friend and Blume (1975) model in interpreting the relationship between age and risk preferences. Their sample consisted of 3 143, 4 299 and 4 442 households from the 1989, 1995 and 2001 SCF's respectively and part of their analysis included the estimation of their model using a maximum likelihood Tobit and probit regression (Jianakoplos and Bernasek, 2006: 992). Jianakoplos and Bernasek (2006: 999) found that risk appetites decreased with age. Their results showed that, *ceteris paribus*, older investors were found to take less risks compared to younger investors and this was the case for both observed and stated willingness to take risk.

Contrastingly, some studies have found the relationship between age and risk aversion to be negative (i.e. as an individual ages they become more risk loving) or for there to be no relationship at all. A study by Wang and Hanna (1997: 27) dealt purely with the topic of how age effects risk tolerance and tested the life-cycle investment hypothesis. Using a similar methodology to that of Schooley and Worden (1996) and Morin and Suarez (1983) in calculating the ratio of risky assets to net wealth, where risky assets were defined in the study as those that provide an uncertain nominal cash flow (Wang and Hanna, 1997: 28), risk tolerance levels were calculated using data from the 1983-89 panel of the SCF. The data was analysed by using a heteroscedastic Tobit model which, according to Wang and Hanna (1997: 28), accounted for the econometric issues of heteroscedasticity and censoring which were encountered in the studies by Morin and Suarez (1983), Schooley and Worden (1996) and Friend and Blume (1975) who all used an Ordinary Least Squares (OLS) regression technique.

The results of Wang and Hanna's (1997) study were particularly interesting. They found that age was significantly related to investments in risky assets and therefore, risk tolerance (Wang and Hanna, 1997: 29). With regards to households with a head who is not retired, the predicted proportion of wealth invested in risky assets was zero percent at age 30 but this followed an upward trend and reaches 24 percent at the age of 80. Households with heads that were retired were predicted to hold zero percent at age 40 increasing to 19 percent at age 80. See Figure 3-1 below for a graphical illustration of these results. Although the predicted proportion of wealth invested in risky assets by households with retired heads was smaller relative to those with heads who have not retired in both instances, there was an increasing trend, therefore, implying that risk aversion decreases with age or, alternatively, risk tolerance increases with age. This suggests that, based on the study by Wang and Hanna (1997: 30), the life-cycle hypothesis should be rejected and in fact risk tolerance increases with age.

Figure 3-1: Predicted Risky Asset Proportion of Total Wealth, by Age and Retirement Status



Source: Wang and Hanna (1997: 29)

The Grable and Lytton (1999b: 1) study provided interesting results as to how risk tolerance interacted with various characteristics of individuals. The authors stated that the purpose of the research paper was threefold in that it "report[ed] the findings of a research project that was designed to (a) determine whether a set of demographic, socioeconomic, and attitudinal variables could be used to distinguish between levels of financial risk tolerance; (b) determine which variables contributed the most to the separation of sample respondents with above-average risk tolerance from those with below-average risk tolerance; and (c) determine if a linear combination of these variables could be developed to predict a person's risk tolerance" (Grable and Lytton, 1999b: 2).

The data used in this study was obtained from a survey of employees of a research university located in the US in 1997. Of the original 2 000 questionnaires sent out, a total of 1 075 (54%) of the returned questionnaires were usable. The questionnaire consisted of a total of 33 questions, 20 of which concentrated on measuring risk tolerance and the remaining 13 items dealing with the demographic, socioeconomic and attitudinal factors (Grable and Lytton, 1999b: 3). The risk tolerance measurement tool was said to be multi-dimensional as it included questions based on a number of risky personal finance situations. The responses to these questions were weighted accordingly and used to determine a risk tolerance index. The weighting of the response depended on the riskiness of the response, where a higher rating meant higher risk and *vice versa*. The sum of the weights resulted in a score on the risk tolerance index (Grable and Lytton, 1999b: 4). The scores ranged from 19 to 63 with a mean of 37 and therefore, the authors created a dichotomous dependent variable with those with scores above 37 coded as 1 and those below 37 coded as 0. Based on the mean of 37, 52 percent of the respondents were classified as having above average financial risk tolerance and the other 48 percent as having below average financial risk tolerance (Grable and Lytton, 1999b: 4). The statistical method used to analyse the data was that of discriminant analysis.

The study found that, contrary to popular belief, older individuals exhibited higher risk tolerance levels in their sample. Further conclusions drawn from the study were that any inferences that increasing age automatically translates to lower levels of financial risk tolerance were possibly incorrect and that age in fact accounts for a small amount of fluctuation in risk tolerance attitudes (Grable and Lytton, 1999b: 7).

In a recent study by Al-Ajmi (2008: 16), the author stated that the primary aim of the research was to improve the understanding of the underlying factors that influenced the investment decisions of individual investors in Bahrain. The study provided important insights as to why and how certain factors affect risk tolerance particularly within the context of Bahrain being considered an emerging economy. The hypothesis that there was no significant difference in risk tolerance across different age groups was tested in the study (Al-Ajmi, 2008: 18-19).

Al-Ajmi (2008: 19) conducted a survey using a questionnaire adapted from one developed by Dow Jones & Company in 1998. The questionnaire consisted of two parts. The first of which dealt with the social and demographic characteristics of the respondents such as, but not limited to, gender, education, age and income. The second part of the questionnaire consisted of eight questions or scenarios with respondents required to select one of three possibilities. The possibilities were given weights from one to three and this allowed for a respondent's risk aversion level to be calculated by summing the weights from the answers given. The reliability of the instrument was tested by determining the Cronbach alpha coefficient which yielded a result of 0.820, which indicated a high internal consistency. Al-Ajmi (2008: 19) mentioned that "[r]eliability refers to how free an item or a scale is from measurement error." Of the original 2 700 questionnaires distributed 1 484 of those returned were usable, in that they were valid and completed, with the response rate being high enough for statistical reliability and generalisability. The responses were then in turn coded and analysed. Al-Ajmi (2008: 19) explained the ranking of the risk tolerance levels as those scoring between 9 and 14 points deemed to be conservative (low risk tolerance) investors, those between 15 and 21 points as moderate (average risk tolerance) investors and those who scored between 22 and 27 points fell in the above average risk tolerance category. The results for the study were obtained through the use of univariate analysis and analysis of covariance.

Al-Ajmi's (2008: 21) results suggested that there was no clear direction in terms of the effect age had on risk tolerance, even though between each age group the results were significantly different. More specifically, it was found that respondents in the age category of between 20 and 29 years had a mean risk tolerance of 1.75 points which was greater than the 30 to 39 years category (mean of 1.68 points) and the category of 50 years or more (mean of 1.72 points). However, the category consisting of respondents between the age of 40 to 49 years recorded the highest level with a mean of 1.82 points (Al-Ajmi, 2008: 20). The differences in the results could, according to Al-Ajmi (2008: 21), be attributed to changes in the financial commitments of the age groups where those in their early working life and before getting married show more risk tolerance, whilst after getting married and having children they become slightly more risk averse. As their children grow older and become less reliant and more financially secure, risk tolerance increases, whilst when individuals approach retirement age, or do in fact retire, they appear to be less risk tolerant. Al-Ajmi's (2008: 22) final conclusion as to how age impacted levels of risk tolerance was that it is complex in contrast to the findings of earlier studies. A further study that found that there was no significant relationship between age and risk tolerance was the research conducted by Hanna *et al* (2001: 59). According to Hanna *et al* (2001: 56) their study used a modified version of the Barsky *et al* (1997) questionnaire and they received 390 valid responses.

Anbar and Eker (2010: 505) investigated whether financial risk tolerance had any link with demographic factors. The sample consisted of 1 097 Turkish university students and the Grable and Lytton (1999a) 13-item instrument was used to determine individual scores of risk tolerance. Using a t-test and ANOVA (Analysis of Variance) it was found that age had no significant effect on financial risk tolerance levels (Anbar and Eker, 2010: 514). Although, logic would suggest that risk tolerance should decrease with the age of an individual, and there have been studies that have found this to be true, one should also consider that there have been other studies that dispute this relationship. The lack of accord as to the relationship between age and financial risk tolerance shows that more research on this variable is appropriate.

3.2.1.2 Race

It is believed that an individual's race or ethnicity can potentially be a determinant in the amount of risk incurred (Yao, Gutter and Hanna, 2005: 58), however, the evidence as to which race group is the most risk tolerant is conflicting. Riley and Chow (1992: 32) investigated whether a number of demographic characteristics, including race, impacted on individuals' asset allocations and thus, their risk profiles. The analysis in this particular study was done using data from the Survey of Income and Program Participation which is "…a longitudinal survey that provides information on the economic status of U.S. households" (Riley and Chow: 1992: 32). The interviews that formed part of this survey were conducted every four months over a two and a half year period and usually investigated four asset classes which were listed as: personal property, real estate, bonds and risky assets. Using the asset allocation data Arrow-Pratt RRA coefficients were calculated, which was measured as the ratio of risky assets to wealth. Riley and Chow (1992: 34) defined a relative risk aversion index as "[a]n empirical measure estimated as one minus the ratio of an individual's risky assets to his total wealth." This is shown as follows (for the kth investor):

$$\begin{aligned} \text{Relative Risk Aversion Index } (RRAI_k) &= (1 - \text{Risky Assets/Wealth}) \\ &= (1 - MPR/RRA), \qquad (3\text{-}1) \end{aligned}$$

where MPR represents the market price of risk, which was assumed to be constant for all investors. Accordingly, the RRAI rises as wealth increases leading to an increase in

RRA and *vice versa*. An increase in the RRAI therefore, obviously translates into a higher level of risk aversion. An individual characterised by a higher level of risk aversion would naturally invest a smaller proportion of their wealth in risky assets and instead they would rather seek investments viewed as being low risk (Riley and Chow, 1992: 34).

Based on the above model, Riley and Chow (1992: 34) found that the differences across racial categories in terms of risk tolerance were small. The four race categories being that of White, Black, Asian and Native American who, as their proportion of risky assets, held on average 4.6 percent, 2.3 percent, 4.5 percent and 2.4 percent respectively (Riley and Chow, 1992: 35). This meant that the RRAI for each category, in the same order, was 95.4, 97.7, 95.5 and 97.6 therefore, illustrating the fact that levels of risk aversion were very similar across the different race groups (Riley and Chow, 1992: 36).

The study by Schooley and Worden (1996: 93), discussed in the previous section (3.2.1.1), divided respondents to the 1989 SCF survey into four race groups: White, Black, Hispanic and Asian/American Indian/Other. Their findings showed that Hispanics had the highest value of risky assets per dollar of wealth with Whites having the lowest and the other groups falling in between. Barsky *et al* (1997: 550), discussed in further detail in section 3.2.1.7, supported this argument as their findings also concluded that Whites were the most risk averse, Blacks and Native Americans were less risk averse and Asians and Hispanics were the least risk averse (or most risk tolerant).

An interesting study on the impact certain demographic factors had on risk tolerance was completed by Bellante and Green (2004: 269). This particular study investigated, as its main research problem, RRA amongst the elderly, whilst further analysis of the relationship between risk aversion and race, gender, education, health status and the number of children was also conducted (Bellante and Green, 2004: 269). The reason for the focus being on those individuals perceived to be old was that in most previous studies examining the effects of age, or the life cycle hypothesis, the samples of respondents considered elderly (generally over 65 years of age) have been small (Bellante and Green, 2004: 270).

In terms of their actual study Bellante and Green (2004: 271-272) used the Arrow-Pratt RRA measure in their model which was followed from the previous studies by Morin and Suarez (1983) and Bellante and Saba (1986) (both of which used an adaptation of the Friend and Blume (1975) framework). The data on portfolio allocation of the elderly was gathered from the Asset and Health Dynamics Among the Oldest Old (AHEAD) database of households with at least one member over the age of 70 years living in the United States between 1993 and 1994 (Bellante and Green, 2004: 271 and 274). After excluding certain households, due to reasons such as a spouse being below the age of 66 years or having missing relevant variables, the final study sample was narrowed down to 4 260 households (Bellante and Green, 2004: 274). In investigating the race variable, the authors only analysed the categories of White and non-White in order to establish whether there were significant differences, *ceteris paribus*, in levels of financial risk tolerance (Bellante and Green, 2004: 273). It was postulated that there would be a difference, as historically the stock market participation of Whites is greater than that of non-Whites. The variable NON-WHITE was included in their analytical model and a negative coefficient was expected, where this represents a lower risk tolerance level amongst non-Whites compared to Whites.

The model, along with certain variations, was estimated using OLS and consistent with the original hypothesis, the coefficient on the variable NON-WHITE was negative and significant in three of the four variations at the one percent level, whilst being significant at the five percent level in the fourth variation (Bellante and Green, 2004: 275-276). Based on the results it was concluded that non-Whites "invest[ed] 3.22% less in risky assets than do Whites" (Bellante and Green, 2004: 277). However, further analysis when housing was included in the definition of a risky asset, similar to previous studies, showed that risk aversion was in fact lower for non-Whites than Whites (Bellante and Green, 2004: 278). It was, nevertheless, argued by Bellante and Green (2004: 280) that housing should be treated as a riskless asset amongst the elderly and therefore, a negative sign for the coefficient on NON-WHITE implying a greater risk tolerance for Whites, was consistent with their expectations.

The purpose of the study by Yao *et al* (2005: 51) was to specifically investigate the relationship between financial risk tolerance and race and ethnicity. The authors highlighted the pertinence of proper investment strategies as individuals with a low risk tolerance may potentially suffer in retirement, whilst, on the contrary, aggressive investors could also expose themselves to large losses in the short term. This particular study chose to analyse the difference in risk tolerance levels between Hispanics, Blacks and Whites in order to raise awareness about the possible implications of further wealth differences across the racial groups. Furthermore, the authors also sought a better understanding of effective financial education programs (Yao *et al*, 2005: 51).

As Yao *et al* (2005: 53) defined risk tolerance as a measure of the willingness to take on financial risk they therefore, concentrated on willingness to take financial risk as opposed to portfolio allocation in determining risk tolerance levels. The reasoning for this approach, was that "…financial risk tolerance may predict future financial behaviour better than current portfolio allocation, especially for disadvantaged groups with no current investments" (Yao *et al*, 2005: 53). The use of hypothetical scenarios to determine risk tolerance levels were argued as being more reasonable as results were based on expectations rather than behaviour and, thus, individuals with no investment assets were able to indicate their preferred level of risk tolerance if it were achievable given the financial resources available to them.

Yao *et al* (2005: 54) hypothesized that Whites had the highest financial risk tolerance compared to the other racial classifications due to factors such as cultural experiences, values and socialisation of minorities impacting on risk attitudes. In addition they expected that Hispanics would have had a lower risk tolerance than Blacks due to the language barrier and the fact that some families may have resided in the US for a shorter period and were, therefore, less comfortable with investing. It is also further acknowledged that some differences may have arisen due to other factors such as education, income and age but multivariate analyses were used to control for these variables and to test whether cultural differences in risk tolerance did exist (Yao *et al*, 2005: 54).

In order to test the above listed hypotheses a combination of the SCF datasets from the years 1983, 1989, 1992, 1995, 1998 and 2001 were used and in total there were 23 243 observations (Yao *et al*, 2005: 54). In order to categorise respondents into risk tolerance groups the SCF financial risk tolerance question was used which asks individuals, when investing or saving money, to indicate whether they would prefer to: take substantial risks expecting substantial returns; take above average risks expecting above average returns; take average risks expecting average returns; or to take no risk at all (Yao *et al*, 2005: 54-55). The data gathered from the surveys was then analysed using a cumulative logit model, motivated by the fact that the SCF financial risk tolerance question has a natural order (Yao *et al*, 2005: 55). Two further categories of risk were created by Yao *et al* (2005: 55) being that of high risk and some risk, where high risk included the substantial and above average risk levels from the SCF risk tolerance question. The some risk category included the substantial, above average and average risk levels.

Descriptive statistics shown in the study suggested that White investors were significantly more likely to take on some risk (59% of all White respondents) compared to Blacks (43%) who were significantly more likely to take on some risk than Hispanics (36%). Interestingly, this was reversed when considering substantial risk as White respondents were least in favour of taking substantial risk (4%), followed by Blacks (5%) and finally, Hispanics (6%) (Yao *et al*, 2005: 55-56). On the other hand, the results from the cumulative logit model, after hypothesis testing, found that whilst there was no significant difference between Blacks and Hispanics with respect to substantial risk, Whites were significantly less likely to select this level of risk (opposed to the original hypothesis). In terms of high financial risk there was no significant difference between all three groups. Finally, the investigation into levels of some risk found that Whites were significantly more likely to choose this level as opposed to Blacks who were in turn significantly more likely to select some risk compared to Hispanics. These results were almost identical to the hypothesis testing conducted using z-tests (Yao *et al*, 2005: 56-57).

The authors discussed that one possible reason for Blacks and Hispanics favouring the substantial risk category was due to their aspiration to reduce the gap in the standard of living or income inequality. The reason for Whites having the greater propensity for some risk could be explained by the low participation by Hispanics and Blacks in the financial markets (Yao *et al*, 2005: 58).

Another study that investigated the relationship between race and risk tolerance was that by Sahm (2007: 3) who used a set of hypothetical gambles over lifetime income to elicit factors that caused individual risk appetites to change. The gamble scenarios were sourced from the Health and Retirement Study (HRS) for the period 1992-2002 in the US. In order to determine individual risk tolerance levels and the changes in these levels, the expected utility theory was used. The theory, according to Sahm (2007: 10), allows for the calculation of a standard metric of risk preference which was the coefficient of RRA (as per the Arrow-Pratt framework). The coefficient may differ across individuals, however, it was assumed to remain constant for a specific individual for all values of permanent consumption (Sahm, 2007: 11).

The analysis method used in the study was that of maximum-likelihood estimation and from the reduced-form model, Sahm (2007: 15) was able to assess how race, and the other factors investigated, affected risk tolerance levels of individuals. Respondents were divided into three racial or ethnic categories which were Black, Hispanic and White (Sahm, 2007: 23 and 39). The findings from the study suggested that there was a major difference between the risk tolerance levels of Blacks and Whites, whilst the difference between Hispanics and Whites was not very large (Sahm, 2007: 23 and 39). More specifically, Blacks were found to have a risk tolerance level that was 28 percent less than that of Whites. Hispanics were lower than Whites by only four percent (Sahm, 2007: 39).

Some important conclusions drawn by Sahm (2007: 29) were that risk tolerance varies both across individuals and time. Furthermore, it was concluded that characteristics that are constant over time, such as gender and ethnicity, explained most of these differences but factors that do change, such as age and economic conditions, may also cause changes in risk tolerance levels (Sahm, 2007: 29). Sahm (2007: 30) stated that these differences have important implications for studying risk preferences, particularly in that there is a "...need for a survey measure of these differences."

One can see from the conclusions drawn from the studies discussed in this section that there is contrasting evidence for the relationship between race and risk tolerance. There is no clear link between being a member of a certain ethnic group and being more or less risk tolerant than another group, further research on the interaction between race and risk tolerance is supported.

3.2.1.3 Income and Wealth

One would expect that as an investor's income and wealth increases they would be able to uphold a higher degree of financial risk (Cohn *et al*, 1975: 610) but the converse to this may also be true. In the former case the perception may be that as an individual attains higher income or wealth his/her ability to tolerate losses is greater, whilst on the other hand an investor may become more prudent with higher income or wealth so as to avoid losing their hard-earned wealth (Hallahan *et al*, 2004: 58). Previous research, however, favours the existence of a positive relationship between income and wealth and risk tolerance, which can also be read as a negative relationship when risk aversion is considered, as is shown below.

It is important to note that there is a difference between income and wealth where income can be defined as the amount of money earned in a certain period in the form of wages, salaries or profits (as examples) by an individual or household (Hartog *et al*, 2000: 10). Wealth represents an individual's net worth and Morin and Suarez (1983: 1204) define this as the difference between a person's total assets and total indebtedness. However, it has been suggested by Cohn *et al* (1975: 610) and Hallahan *et al* (2004: 58) that the two factors are strongly correlated. Based on the relatedness of the two factors the study by Al-Ajmi (2008: 21) is an example where monthly incomes were used as a measure of wealth. Although it is acknowledged that the two factors are inherently different, in the following review the effects that income and wealth have on risk tolerance are examined together.

The study by Morin and Suarez (1983: 1210), discussed in more detail in section 3.2.1.1, found that when controlling for life-cycle effects, households in the upper wealth group showed a trend of DRRA. Additionally, in their study wealth was found to be the most important variable in determining risk aversion levels. A study by Bertaut (1998: 264) into the stockholding behaviour of households in the US compared the same households six years apart in analysing their investment behaviour. The purpose of the analysis was partly to determine whether portfolio allocation changed over the period due to household characteristics and major life changes (Bertaut, 1998: 264). The sample of 1 368 households was obtained from the 1983 and 1989 SCF's and a bivariate probit model was used as it "...allows [for] not only the calculation of the probabilities of stock ownership in both 1983 and 1989, but also of the conditional probabilities of continued participation or non-participation" (Bertaut, 1998: 267). According to the stockholding behaviour of households, Bertaut (1998: 273) concluded that, "[f]ormal econometric analysis shows that households with lower wealth and higher risk aversion are less likely to hold stocks…"

Grable and Lytton (1999b: 4), discussed previously in section 3.2.1.1, investigated the relationship between income and risk tolerance. After conducting an F-test on the data it was found that income was a significant factor in differentiating between levels of risk tolerance, along with all the other explanatory variables except marital status (Grable and Lytton, 1999b: 5). In terms of which variables were the most important in differentiating between risk tolerance levels, income was the third most influential after education and financial knowledge respectively. Furthermore, a positive income coefficient meant that a higher level of income was related to an above average level of risk tolerance (Grable and Lytton, 1999b: 6). Research pertaining to the third hypothesis noted in section 3.2.1.1, concluded that the predictive power using discriminant scores was consistently good across the above average and below average risk categories and overall, it achieved correct classifications of 70.33 percent of the respondents (Grable and Lytton, 1999b: 6). Based on these results it can therefore, be seen that there is more evidence in favour of a positive relationship between risk tolerance levels and income levels.

A study by Hartog *et al* (2000: 1), along with developing an appropriate measurement of individual risk tolerance, investigated whether individual risk aversion decreases as income and wealth increases. The measurement technique used by Hartog *et al* (2000: 3) used expected utility theory to deduce the Arrow-Pratt measure of absolute risk aversion which is explained in section 2.2.1. In order to do this, respondents in the study were asked to indicate a reservation price for a lottery ticket where there was a specified probability of winning a prize of particular value. By denoting the lottery prize as Z, the probability of winning as α, the reservation price as λ and assuming a twice differentiable, concave utility function U(W) in wealth W the Arrow-Pratt measure of absolute risk aversion could then be calculated by applying various mathematical steps and techniques[1].

According to Hartog *et al* (2000: 4) the lottery question was used in three data sets listed as the Brabant Survey, the Accountants Survey and the GPD Newspaper Survey. The Brabant Survey is explained as a follow-up survey originally conducted in 1952 on children 12 years old and in sixth grade in the province of Noord-Brabant in the Netherlands. The follow-up surveys were completed in 1983 and 1993 when the lottery question was included. In total there were roughly 2 800 respondents who answered questions pertaining to their family background, IQ, schooling, labour market career and family situation (Hartog *et al*, 2000: 5).

The Accountants Survey consisted of a mailed questionnaire to 3 000 out of 9 000 accountants listed in the National Register of Chartered Accountants in the Netherlands (Hartog *et al*, 2000: 5). This was conducted in 1999 and a total of 1 599 accountants responded to the questionnaire. According to Hartog *et al* (2000: 5) the purpose of the survey was to "assess the effect of different educational routes to qualification" and the questions focused on education, work experience, earnings and personal characteristics. In both the Brabant Survey and the Accountants Survey the following question was asked (Hartog *et al*, 2000: 5):

"Among 10 people, 1000 guilders are disposed of by lottery. What is the most that you would be willing to pay for a ticket in this lottery?"

The third survey, the GPD survey, was a regional newspaper circulated survey consisting of a two-page questionnaire and was administered in January 1998 (Hartog *et al*, 2000: 5). The questions related to factors such as income, work, health, politics and personal characteristics and there were 25 000 respondents in total. It was noted by Hartog *et al* (2000: 5 and 17) that this particular survey unfortunately, did not include the lottery question listed above but six other variations of the lottery question were used. The lottery questions varied in both the number of participants and the prize

[1] See Hartog *et al* (2000: 3-4).

(Hartog *et al*, 2000: 17) and obviously, with a change in the number of participants the probability of winning would also change.

All three of the data sets were modelled using regression analysis. In particular the procedures used were those of OLS estimation and the Heckman two-step method using Maximum Likelihood estimation (Hartog *et al*, 2000: 9-19). When analysing the Brabant Survey data, Hartog *et al* (2000: 10) concluded that the relationship between income and risk aversion was negative, as well as the relationship between wealth and risk aversion, lending support to the belief that risk tolerance increased with income and wealth. The result in the Accountants' survey was different, however, as it was concluded that there was no relationship between risk aversion and income (Hartog *et al*, 2000: 12). This was attributed to the fact that the respondents were largely homogenous in characteristics and there was very little variation in income across the surveyed individuals. In the GPD Newspaper Survey it was found that risk aversion fell as income increased, providing further motivation that there was a positive relationship between financial risk tolerance and income and wealth (Hartog *et al*, 2000: 14).

Schooley and Worden (1996: 96) discussed in more detail previously in section 3.2.1.1, also found that as a household's level of wealth increased so did their risk tolerance level or more specifically, their holdings of risky assets. Hallahan *et al* (2004: 67) also provided further evidence that wealth and risk tolerance exhibited a positive relationship.

A study by Christiansen, Joensen and Rangvid (2009: 1) investigated, as the main purpose of their research, whether there were any gender differences in risk tolerance levels. However, in their analysis other variables such as age, children living at home, education and income were also examined in their simple and extended models (Christiansen *et al*, 2009: 4 and 7-9). The data employed in the study comprised a random sample of 10 percent of the population of Denmark over the period 1997 to 2004 and, according to Christiansen *et al* (2009: 4), "the data set is hosted by the Danish Institute of Governmental Research (AKF), and it stems from Statistics Denmark, which had gathered the data from different sources, mainly from administrative registers." The sample consisted of 3 023 110 observations of decisions made by individual investors who were 18 years or older. The data was said to form an unbalanced panel data set, as over the period some individuals would have turned 18 and entered the data set, whilst others would have died or emigrated (Christiansen *et al*, 2009: 4).

The particular data set used by the authors allowed them access to certain income and financial variables of the individuals and these included non-capital income, cash holdings, value of stock holdings, value of bond holdings, equity in houses and annual pension contributions. A key point highlighted by Christiansen *et al* (2009: 4) was that on average, the men in the data set had higher levels of income and wealth than the women and this difference was even greater when comparing married men and women. Furthermore, they also found that men were more likely to actively participate in the financial markets (27% of men own stocks as opposed to 23% of women) and, as was the case with income, the difference was more pronounced when comparing married men and women. Over and above this, when investing, men also held a larger proportion of stocks or had greater stock holdings when compared with women.

Christiansen *et al* (2009: 22) used a bivariate probit model to estimate both the simple and the extended model. The extended model included the explanatory variables cash holdings, equity in houses and pension contribution (Christiansen *et al*, 2009: 9) over and above those included in the simple model. The findings from the simple model showed that income was positively related with the stock market participation decision as well as participation in the bond market and therefore, it was concluded by Christiansen *et al* (2009: 8) that individuals who had greater wealth levels were more likely to invest in the financial markets. Finally, the conclusions drawn from the extended model were consistent with that from the simple model even after the inclusion of the additional control variables (Christiansen *et al*, 2009: 9). The bond and stock market participation decision was also found to be positively related to each of the three new variables, cash holdings, equity in houses and pension contribution, and therefore, there is further support for the notion that the more wealthy an individual is, the greater the probability of them becoming financial market participants (Christiansen *et al*, 2009: 9).

Further support for the existence of a positive relationship between financial risk tolerance and income and wealth was provided by the following studies which have already been discussed in more detail in previous sections. Riley and Chow (1992: 34) found that there was a negative relationship between risk aversion and income (i.e. the relationship between risk tolerance and income was positive) and added that low income families were the most risk averse when measured by the RRAI. Similarly, Yao *et al* (2005: 56) found that income had a positive effect on the willingness to take on levels of financial risk. Al-Ajmi (2008: 21-22) also found that "higher-income earners have a significantly higher appetite for risk than lower income earners."

However, it must be noted that Pålsson (1996: 785) found, in her study, that RRA exhibited a constant relationship with respect to wealth. The purpose of the study was to investigate whether the coefficient for RRA was affected by socio-economic, geographic or demographic variables (Pålsson, 1996: 781). The sample used by Pålsson (1996: 778) consisted of cross-sectional data for 9 508 Swedish households for the year 1985. Two models were estimated in the Pålsson (1996: 778) study, where the first excluded households which held no risky assets in the portfolios (1 604 households) and the second further excluded 832 households who indicated "...an average tax rate on total taxable income below 100 percent..." The models were estimated using the OLS technique (Pålsson, 1996: 781).

Pålsson (1996: 783), amongst other variables, included household net wealth and household income in the form of continuous independent variables in the model. The results from both the models estimated showed very low explanatory power (adjusted R-squared coefficients of 0.01) and using a two-tailed test, no independent variables were significant at the five percent level (Pålsson, 1996: 785). Based on the results, Pålsson (1996: 785) concluded that "...relative risk aversion is constant with respect to wealth." Another finding mentioned by Pålsson (1996: 785) was that the wealth elasticity of money demanded was greater than one and this also supported constant, or increasing, RRA. Overall, it was stated that the primary findings of the study suggested the "...degree of relative risk aversion is not systematically correlated to any of the included economic variables such as net wealth, income and taxes" (Pålsson, 1996: 786). It must be noted though, that Sweden is a very flat society with greater levels of income equality compared to other countries (Gottschalk and Smeeding, 1997: 636 and Coburn, 2004: 47) and this may have affected the results.

From the review of the studies above it can be seen that there is strong evidence for the existence of a positive relationship between income and wealth and risk tolerance levels. Although, it seems the interaction between risk tolerance and income or wealth is straightforward there has been limited research on this from a South African perspective. This will become more evident in the discussion of the South African studies in section 3.2.2.

3.2.1.4 Gender

Previous research on the topic of gender and financial risk tolerance has been extensive and generally concluded that women were more risk averse than men and that men favoured more risky assets compared to women (Pålsson, 1996: 785, Hartog *et al*, 2000: 11, Hallahan *et al*, 2004: 67 and Al-Ajmi, 2008: 21-22).

Powell and Ansic (1997: 610) conducted two computer-based experiments, using a set of practical financial decisions, in order to determine whether women were less risk tolerant than men. The first experiment consisted of insurance cover decisions, whilst the second was based on currency market decisions (Powell and Ansic, 1997: 611). The sample for the insurance cover experiment was drawn from university students and included 64 males and 62 females (Powell and Ansic, 1997: 612), whilst the currency market experiment included 66 males and 35 females (Powell and Ansic, 1997: 618). The findings from both experiments concluded that females had a much higher risk aversion level than males, regardless of the degree of familiarity, frame or cost (Powell and Ansic, 1997: 622).

In the study by Embrey and Fox (1997: 33), the authors focused on women who were living alone and therefore, the investment decisions of other household habitants were controlled for, allowing for a more meaningful analysis between the investment decisions of males and females. The data used in the study was taken from the 1995 SCF survey and from the total of 4 299 households there were 839 single-person households (Embrey and Fox, 1997: 34). Only single-person households were selected as most of the households with more than one member were male headed and secondly, by using these households, the "…differences in investment decision-making that may exist between men and women can be better isolated" (Embrey and Fox, 1997: 35).

The hypotheses tested in the study were, firstly, that women were more risk averse than men, through their choice of less risky investments and secondly, that single men and women had the same basic determinants of investment decisions (Embrey and Fox, 1997: 36). Multivariate analysis, using a Tobit model, was used to estimate the parameters in the study (Embrey and Fox, 1997: 35). An analysis of the percentage of males and females who invested in assets categorised as that of no risk, average risk, above average risk and substantial risk was also done. The results from this step showed that 62 percent of the women in the sample favoured the no risk category as opposed to 34 percent of the males. For the combination of average and above average risk close to 60 percent of the men chose this category compared to 36 percent of the females. Eight percent of the males and only three percent of the females selected the substantial risk category (Embrey and Fox, 1997: 36). Another result was that females invested in more assets classified as having little risk compared to males, whilst the result was reversed for investing in risky assets. Although, from their various analysis techniques, Embrey and Fox (1997: 38) concluded that men were more risk tolerant than women in that they invested more in risky assets, it was also found that gender was not the critical determinant of investment choice. Wealth, measured by net worth and the expectation of an inheritance, was in fact found to be the more critical determinant in investment decisions.

Sunden and Surette (1998: 207) conducted a study investigating gender differences and asset allocations using a sample of 3 906 households from the 1992 SCF and 4 299 households from the 1995 SCF. Analysis using a multinomial logit and probit model indicated that investment decisions were not driven by gender alone but rather a combination of gender and marital status (Sunden and Surette, 1998: 209). It was concluded by Sunden and Surette (1998: 210-211) that gender did significantly affect allocations into defined-contribution (DC) pension plans, in that men were more likely to have DC plans. They further acknowledged that their results should be viewed as descriptive rather than causal (Sunden and Surette, 1998: 211).

Dwyer, Gilkeson and List (2002: 152) examined the relationship between gender and risk preferences of a sample of mutual fund investors in 1995. Using an ordered probit model, Dwyer *et al* (2002: 155-156) found results that suggested men exhibited more appetite for risk than women when choosing mutual funds. Eckel and Grossman (2002:

282) used experiments to measure risk tolerance "...as the variance in possible payoffs associated with a given choice." Their sample consisted of 204 participants who each completed a Zuckerman Sensation-Seeking Scale (SSS) survey and gamble choices (Eckel and Grossman, 2002: 286). The SSS survey results suggested there were no significant gender differences in risk taking, however, the gamble choice experiment found that women were significantly less risk tolerant than men (Eckel and Grossman, 2002: 287-288).

The study by Coleman (2003: 99) used the 1998 SCF to compare the risk appetites of women to men and to determine whether women showed higher levels of risk aversion and, following from this, whether they favoured investing in less risky assets. A univariate analysis comparing men and women was conducted by Coleman (2003: 102), however, the main hypothesis was tested using a multivariate analysis (Coleman, 2003: 104). This hypothesis was whether investor characteristics influenced risk attitudes and risky asset investments. The particular analysis method used in the study was a logistic regression estimated three times with the dependent variable representing different levels of risk in each model (high risk, some risk or no risk). The use of a logistic regression was motivated by the fact that the dependent variables were dichotomous (0,1) variables (Coleman, 2003: 105).

The results from the study drew the following conclusions. Firstly, it was found that women illustrated a higher level of risk aversion when compared to men. This was based on the fact that women were significantly more likely to accept no risk as opposed to accepting high risk in exchange for high returns using the SCF question (Coleman, 2003: 106). The author then investigated whether these reported findings were in fact correlated to investment behaviour by examining women's holdings of stocks or stock mutual funds (considered to be investment options with high risk). Respondents were divided into two age related categories, below 40 and greater than or equal to 40, and the findings suggested gender was not a significant variable in either category (Coleman, 2003: 108). Based on this, women were just as willing as their male counterparts to invest in stocks or stock mutual funds, when controlling for other factors (Coleman, 2003: 109). Furthermore, Coleman (2003: 109) also investigated the ratio of risky assets to net worth for the same age categories. The findings from this step of the analysis were that there was no significant difference in the ratios for men and women younger than 40. Coleman (2003: 109), did, however, find that women over the age of 40 had a lower ratio than men in the same age category. These findings do show that there is some support for the argument that gender plays a role in determining risk tolerance attitudes.

The Hanna and Lindamood (2004: 31) study used a pension choice measure to analyse the risk aversion levels of 152 students from Ohio State University in 2004. The SCF question was also included in the study and correlations were gathered in order to test the relationship between gender and both the SCF question and the pension choice measure (Hanna and Lindamood, 2004: 31). The analysis results proved that gender had a positive relationship with both measures and therefore, females were more risk averse than males (Hanna and Lindamood, 2004: 34).

Charness and Gneezy (2007: 1) examined whether there were any differences in the risk appetites of men and women or in their own words, "…the interaction of risk-taking with the gender of the decision maker." The authors suggested that previous papers on this selfsame topic may, interestingly, suffer from a selection bias where experiments may be designed in such a way that the researcher obtains the results he/she wishes to obtain, as drawing no conclusions may result in the scrapping of the research (Charness and Gneezy, 2007: 1-2). They argued that a research paper that produces interesting results was far more publishable than one that did not and such a publication bias creates incentives for researchers to design studies that will yield intriguing results (Charness and Gneezy, 2007: 2).

In order to overcome the biases mentioned above, Charness and Gneezy (2007: 2) used the results of previous studies collected systematically, using many observations by researchers in different setups, but based on the same simple investment game. According to Charness and Gneezy (2007: 2), the original data sets were collected with no intention of drawing comparisons and therefore, there was no uniform design, thus allowing for the testing of the robustness of their hypothesis.

The investment game used as part of the methodology was simulated from a study conducted by Gneezy and Potters (1997) and is outlined here (Charness and Gneezy, 2007: 2). In the game an individual investor is given an amount $X and is requested to indicate how much of it, \$x, should be invested into a risky option and how much is to be kept. The amount that is invested earns a dividend of \$kx (k>1) with a probability of p and is lost with a probability of 1 – p. The money kept by the investor or not invested is equal to \$(X – x). The payoffs are then \$(X – x + kx) with a probability of p, and \$(X – x) with a probability of 1 – p. p and k are chosen so that p*k is always greater than one, ensuring that the expected value of investing is higher than the expected value of not investing. This means that a risk neutral or risk seeking individual should invest \$X whilst a risk averse individual should invest less. Choosing x was the only decision made by the respondents in the experiment. Previous studies have consistently found that there was a difference between the two gender groups whereby, males chose a higher x than females (Charness and Gneezy, 2007: 2-3).

In total, Charness and Gneezy (2007: 3-13) examined ten different studies[2] using the same method with only slight variations which were predominantly in the value of p and therefore, 1 – p. All of the studies, except for one, found that men invested more than women and could therefore, be construed as being more risk tolerant. The contrarian study found that there was no difference in risk taking across gender but it was mentioned that this particular study was the only one not conducted in a Western society (villagers in Tanzania and India participated in the study) and there may be different social norms in place (Charness and Gneezy, 2007: 12). The authors conducted a binomial test on the data and even when including the study that found evidence to the contrary, the chances of men investing more than women was significant at the five percent level in both cases. It was significant at the one percent level when the tenth study was excluded (Charness and Gneezy, 2007: 13). Based on their results, Charness and Gneezy (2007: 13) stated that the answer to their research problem was clear, in that females appear to have a lower level of financial risk tolerance than men.

Faff *et al* (2008: 4) used a lottery experiment to determine the financial risk tolerance of 162 participants in their study examining the relationship between financial risk tolerance and risk aversion. Univariate and multivariate empirical analysis techniques were conducted by Faff *et al* (2008: 13-16) and the findings from both models

[2] Yu (2006); Charness and Gneezy (2003); Charness and Gneezy (2004); Langer and Weber (2004); Haigh and List (2005); Fellner and Sutter (2004); Charness and Genicot (2004); Bellemare, Krause, Kroger and Zhang (2004); Dreber and Hoffman (2007); and Gneezy, Leonard and List (2007)

suggested that females were more risk averse than males. Olivares, Diaz and Besser (2008: 1) investigated the relationship between gender and portfolio choice and, thus, risk tolerance, by analysing a selection of pension funds in Chile. The purpose of the paper by Olivares *et al* (2008: 2) was to determine whether there was any variance in the portfolio choice of pension funds between men and women, whilst considering variables such as age, total wealth invested in funds, monthly contribution, types of funds, Pension Fund Administrator and region.

The sample employed in the study consisted of a panel data set of 25 238 respondents obtained from The Superintendence of Chilean Pension Fund Administrators and was evaluated in two different periods in the year 2007 (Olivares *et al*, 2008: 5). The information included data on demographic and financial statistics, whilst there were five types of pension funds included as a variable. These ranged from Pension Fund E, the fund with the least risk, to Pension Fund A, the fund with the most risk (Olivares *et al*, 2008: 5-6). According to their results, Olivares *et al* (2008: 10) found that when considering both age and wealth separately, it appeared that women selected less risky funds or were more risk averse than men. They concluded that the proportion of men in each of the Pension Fund groups choosing portfolios with higher levels of risk was larger than that of females (Olivares *et al*, 2008:11). Other inferences made were that men were more likely to invest larger amounts in riskier portfolios suggesting that retirement cash flows for women would be lower, compounded by the evidence that Chilean women live longer than their male counterparts (Olivares *et al*, 2008: 11). The authors mentioned that this was an extremely important implication that financial managers must consider when designing retirement plans for women (Olivares *et al*, 2008: 12).

Studies have generally found that men are more risk tolerant than women, as can be seen above, however, it is important to acknowledge reasons for this and to recognise some of the implications if assumptions are made based on these results. Gender based differences may be attributed to the fact that financial advisors assume females are generally more risk averse and therefore, they are provided with conservative investment advice, a case of "statistical discrimination" (Bajtelsmit and Bernasek, 1996: 6). Some authors, such as Bajtelsmit and Bernasek (1996: 1) and Bajtelsmit *et al* (1999: 2), described how this could be problematic in the asset allocation decision as women's greater longevity suggests that the period of retirement will be longer for women than men and they would, thus, need to invest more for consumption in retirement. The study by Bajtelsmit and Bernasek (1996: 1) focused on previous research on this topic in examining what was known and unknown about gender based differences in risk tolerance. Bajtelsmit *et al* (1999: 4) used the 1989 SCF to determine whether there were any gender-linked differences in DC pension allocation decisions. Using the Arrow-Pratt RRA measure Bajtelsmit *et al* (1999: 6) found that women allocated less towards their pensions.

Barber and Odean (2001: 261) believe that the reason for males being more risk loving than females was simply due to overconfidence where men are more confident than women when it comes to investing. The study by Barber and Odean (2001: 266) analysed common stock investments of males and females in order to test whether men traded more than women and whether by trading more, portfolio performance suffers. Their findings suggested that men did in fact trade more (men had higher portfolio turnover rates) and this did have the effect of eroding returns (Barber and Odean, 2001: 289). The authors believe the simple, yet powerful, explanation for the "...high levels of counterproductive trading..." is overconfidence (Barber and Odean, 2001: 289).

Bernasek and Shwiff (2001: 345) mentioned that women had a greater chance of being exposed to poverty when they are older. This was because, when compared to men, their lifetime earnings were generally lower and therefore, they were not able to accumulate as much savings or invest similar amounts. Added to this was the greater life-expectancy of women, implying that the little savings females have, in fact need to be spread out over a longer period. Furthermore, Bernasek and Shwiff (2001: 345) claimed that females also experience more chronic health problems in their older years and correspondingly, have to meet higher expenditures. The authors did, however, find in their study that women tended to reduce the amount they invested in stocks and were, therefore, more risk averse (Bernasek and Shwiff, 2001: 355). This was found by conducting an analysis of the percentage of DC pension assets invested in stocks and estimating a two-limit Tobit model to test the relationships between various demographic factors and risk tolerance (Bernasek and Shwiff, 2001: 348-349).

If the evidence that females are investing in less risky assets and portfolios compared to men is true, this could have critical implications for females in their retirement years. If females are not receiving the most accurate investment advice and, in turn, not investing in the most appropriate products their time spent as a retiree may be an uncomfortable phase of trying to minimise expenditures in order to survive on a daily basis. If females are advised to choose, or directed to, investment products characterised by lower risk levels their chances of earning adequate returns on their investments is hindered, possibly curtailing many retirement plans in the process. In this case the old investment adage of high risk equals high return is followed and financial advisors need to be acutely aware of these problems when consulting with females.

Embrey and Fox (1997: 33) stated that, "[the] combination of low-risk investing, lower earnings, little savings and greater needs, presents women and their financial advisors with a significant challenge. While saving more for retirement is good advice, it may not be practical given immediate consumption needs. While expecting to live longer is a benefit of being a woman, it places greater demands on retirement assets. Given that most people would not want to shorten their life spans, and that increasing one's savings rate is difficult for those with low earnings, the remaining component that can be changed to improve the long-term financial outlook for women is the expected rate of return of their investments."

Lugovskyy and Grossman (2007: 1) covered a similar concept as that of statistical discrimination mentioned above but in their case refer to it as gender-based stereotypes. In their study into forecasting risk preferences of women and men, they investigated the predictive power when using gender-based stereotypes in such a situation (Lugovskyy and Grossman, 2007: 4). It was suggested by Lugovskyy and Grossman (2007: 2) that in many cases stereotypes have been used in assessing risk tolerance levels for individuals. They defined stereotyping as "…the act of assigning to a member of a particular group a characteristic or trait based solely on the individual's membership in that group..." and further stated that, "[s]tereotypes may be benign, somewhat accurate, expressions of folk wisdom or may be prejudicial, inaccurate, and used to justify discriminatory behaviour" (Lugovskyy and Grossman, 2007: 2). Although stereotyping may result in correct classification at times, as mentioned by the authors, it was clearly evident that individuals were not treated for their unique selves but rather painted with the same brush as other individuals who may possess a single shared characteristic, such as being female. This can have potentially damaging effects not only in assessing one's risk tolerance but in many other environments too. Lugovskyy and Grossman (2007: 3) did acknowledge though, that if one has no other option but to use stereotypes, assuming it contains some sense of truth, as a predictor it may indeed improve the accuracy of the prediction as opposed to randomly guessing. However, when one does have access to information that is more specific to a certain characteristic or trait this would improve forecast accuracy.

In order to test the validity of risk tolerance forecasts, Lugovskyy and Grossman (2007: 4) used an experiment involving three scenarios where subjects were required to make predictions in each, given certain instances and information. In the first scenario, subjects were provided only visual clues on which predictions were made and this method was sourced from a study by Eckel and Grossman (2008). The second scenario was different in that no visual clues were given to the subjects but they received the other subjects' responses to two questions from the Weber, Blais and Betz (2002) survey on risk-preference (Lugovskyy and Grossman, 2007: 4). The third scenario was a combination of the first two where visual clues and the two answers were given to the subjects (Lugovskyy and Grossman, 2007: 4-5).

In total there were 120 subjects used in the experiment and 45 of them participated in the session for the first scenario, 40 in the second and the remaining 35 in the third scenario (Lugovskyy and Grossman, 2007: 9). Results from the experiment showed that when only visual clues were given and no other information (scenario one), the subjects did in fact base predictions on the gender-based stereotype that women were more risk averse than men (Lugovskyy and Grossman, 2007: 15). In the second scenario it was found that with only the two responses provided, these were used by the subjects in making their predictions, however, in the third scenario it was found that when both sets of information were provided the subjects applied the gender stereotype even though they did not ignore the more relevant information (Lugovskyy and Grossman, 2007: 16). Although these results are interesting, they may have been even more relevant if the same subjects had participated in all three of the scenarios in order to see whether their predictions were vastly different over each case.

Historically, women have been regarded as being more risk averse than males (Powell and Ansic, 1997: 607 and Schubert, Brown, Gysler and Brachinger, 1999: 381), however, "[t]he extent to which these gender differences represent evidence of general traits rather than contextual responses to social and environmental factors is still unresolved" (Powell and Ansic, 1997: 607). The study by Schubert *et al* (1999: 382) used two experiments to examine gender-specific risk behaviour. The first consisted of a series of investment and insurance decisions and was referred to as the contextual treatment (Schubert *et al*, 1999: 382). The subjects in the experiment were 36 males and 32 females. The second experiment, the abstract treatment, consisted of a set of similar decisions presented as abstract gambling choices (Schubert *et al*, 1999: 382). This experiment included 40 males and 33 females. Schubert *et al* (1999: 384-385) found that there was not much difference between the financial risk tolerance of males and females under controlled (experimental) economic conditions and that risk tolerance in financial choices were dependent on the decision frame. The authors further questioned the previous findings that males were more risk loving than females and concluded that the differing risk attitudes "…may be due to differences in male and female opportunity sets rather than stereotypic risk attitudes" (Schubert *et al*, 1999: 385).

Although, the overwhelming majority of studies suggested men had a greater willingness to take on levels of financial risk as opposed to females, who preferred less risk, there was, however, some evidence provided by Schubert *et al* (1999) that suggests contrary to this and therefore, the relationship is not as clear as argued by some authors.

3.2.1.5 Marital Status

The study by Sunden and Surette (1998: 210), see section 3.2.1.3, investigated whether marital status had an effect on the respondents' asset allocation for retirement plans, referred to as DC plans. Their findings were that marital status did in fact have a significant impact on asset allocation. More precisely, they found that married women were the least likely to have a DC plan compared to married men and single women and that single women were more likely to have a DC plan than single men (Sunden and Surette, 1998: 210). Barber and Odean (2001: 285), discussed in the previous section, concluded that single individuals held more volatile (i.e. risky) portfolios than those who were married. Hallahan *et al* (2004: 71), see section 3.2.1.1, also stated that their evidence suggested that single investors were less risk averse and thus, marital status was a significant determinant in financial risk tolerance levels.

Hawley and Fujii (1994: 197-198) conducted an empirical analysis on the factors that determine financial risk preferences using the 1983 SCF survey data. Of the total 3 824 households in the SCF data set, the authors created a sub-sample of 2 456 households who were between the ages of 25 and 62. Their reasoning for this was that they wanted to restrict the analysis to those individuals who were economically active (i.e. not at school and not yet retired) (Hawley and Fujii, 1994: 198).

In a similar fashion to other studies, such as Yao *et al* (2005), researching this and related topics, Hawley and Fujii (1994: 198) used the SCF risk tolerance question which required respondents to indicate their preferred level of risk when investing. As explained previously, the options were no financial risk, average financial risk, above-average financial risk and substantial financial risk. In this case the risk preferences were ordinally defined by assigning a numerical value to rank each level and, as such, the dependent variable, in their study denoted as Z_i, had four discrete values listed as follows:

0 if the respondent was not willing to take any financial risks;

1 if the respondent was willing to take average financial risks expecting to earn average returns;

2 if the respondent was willing to take above-average financial risks expecting to earn above-average returns;

3 if the respondent was willing to take substantial financial risks expecting to earn substantial returns.

Hawley and Fujii (1994: 198-199)

The function $Y_i = X_i\beta$, Y_i taking a value from $-\infty$ to $+\infty$, was then modelled with the vector X representing underlying factors that determine risk preferences (e.g. age, income and marital status) (Hawley and Fujii, 1994: 197-199). The authors then used an ordered logit model which uses maximum likelihood estimation procedures to find values of β and certain thresholds μ_0, μ_1 and μ_2 such that dependent variable Z_i is represented as follows:

$$Z_i = \begin{cases} 0 & Y_i < \mu_0 \\ 1 & \mu_0 \leq Y_i < \mu_1 \\ 2 & \mu_1 \leq Y_i < \mu_2 \\ 3 & Y_i \geq \mu_2 \end{cases} \qquad (3\text{-}2)$$

Hawley and Fujii (1994: 199)

This model, according to Hawley and Fujii (1994: 199), "avoids biases inherent in linear regression models applied to ordinal dependent models."

In analysing whether financial risk tolerance levels were dependent upon economic and demographic factors of individuals, interesting results were discovered as to the effect that marital status had (Hawley and Fujii, 1994: 202). In the study the respondents were divided into six groups which were married men (the base group), married women, male heads of households, female heads of households, single men and single women. Using these six groups the evidence suggested that male heads of households and married men had very similar risk preferences, whilst single men preferred a higher level of financial risk (Hawley and Fujii, 1994: 202). The evidence from the data on females found that married women were in fact the most risk tolerant, or least risk averse, followed by single women and then female heads of households (least risk tolerant) (Hawley and Fujii, 1994: 202).

Chaulk *et al* (2003: 258) investigated how marital status affected individual financial risk tolerance levels both independently and as an interaction variable. The purpose of their research was "…to provide a theoretical basis for understanding how financial risk tolerance is affected by family transitions" using concepts from prospect theory and the theoretical paradigms of family development theory (Chaulk *et al*, 2003: 258). Among the hypotheses tested by Chaulk *et al* (2003: 263-264) were that, "…married individuals will be less risk tolerant than single individuals"; "…the effect of marital status on financial risk tolerance will be greater for men than women"; "…the effect of marital status on financial risk tolerance will decrease with age"; and "…the effect of marital status on financial risk tolerance will be less pronounced when income levels are high". The latter three hypotheses represented the interaction variables. Chaulk *et al* (2003: 266) conducted two studies, the first of which consisted of the 1999 Family and Couples Relationship Survey in Canada and the second was the 1998 SCF in the US. The first study was used more for exploratory purposes whilst the SCF study was used to conduct more rigorous tests of the hypotheses (Chaulk *et al*, 2003: 266). Marital status was treated as a dummy variable in the study and a regression analysis was performed (Chaulk *et al*, 2003: 269).

The results from the second study were inconclusive, in that marital status was found to have no significant relationship with risk tolerance and this was the same for marital status and its interaction with gender, age and income (Chaulk *et al*, 2003: 274). The first study produced more conclusive results for the interaction between marital status and gender but this was when measuring employment risk. Study one showed that, for financial risk tolerance, the interaction between age and marital status was important, as younger married respondents were less risk tolerant than their unmarried counterparts in age and older married respondents were more risk tolerant than their single counterparts in age (Chaulk *et al*, 2003: 275). The authors did acknowledge that their model was only partially supported by their findings but argued that it should not be discarded as further research was necessary, particularly using a more diverse and larger sample and a longitudinal methodology (Chaulk *et al*, 2003: 276).

Hanna and Lindamood (2005: 1) investigated the risk preferences of married couples and focused on the differences between households where the wife responded and households with the husband as the respondent. The method used to determine the risk tolerance levels was the SCF risk tolerance question, previously discussed (Hanna and Lindamood, 2005: 6). Results from the logit regression technique used, concluded that the probability of a female taking some risk was 56 percent as opposed to a similar male whose probability was 68 percent and therefore, wives were less risk tolerant than husbands (Hanna and Lindamood, 2005: 8-9). Hanna and Lindamood (2005: 10) recommended that financial advisors need to assess the risk tolerance of both spouses when dealing with couples and suggested that when the levels differed it may be reasonable to use the average of the two scores.

An interesting study, similar to that of Hanna and Lindamood (2005), was conducted by Gilliam, Goetz and Hampton (2008: 3). They argued that risk tolerance assessments and asset allocation decisions have been made even more complex due to spousal considerations (Gilliam *et al*, 2008: 3). The SCF risk tolerance question was slightly modified and employed to determine risk preference levels and then coded to be used as the dependent variable in a similar technique to Hawley and Fujii (1994). The question was sent as part of a survey which included questions on demographic characteristics to 110 couples in the US (Gilliam *et al*, 2008: 6).

The results from the study suggested that the mean risk tolerance of husbands was significantly greater than that of wives (Gilliam *et al*, 2008: 7). Together with this finding, further tests found that wives, who were university graduates, had higher risk tolerance levels than their husbands, however, their husbands' mean risk tolerance score was lower than that of the husbands whose wives were not university graduates (Gilliam *et al*, 2008: 7-8). Gilliam *et al* (2008: 9) noted in the implications of their study that financial advisors should be wary of using demographic characteristics as a heuristic (stereotyping) for determining individual risk tolerance levels and should not assume husbands are more risk tolerant than wives. It was recommended that spouses should be educated on their perception of risk and have their risk tolerance levels assessed before any assumptions are drawn by financial advisors (Gilliam *et al*, 2008: 10).

It was mentioned that financial advisors need to assess the risk tolerance of couples in different ways and particularly when the risk tolerance levels differ between the two it can be extremely difficult to determine an appropriate measure for both (Gilliam *et al*, 2008: 10). Some financial advisors are believed to average the scores for both the husband and the wife and use that as a combined risk tolerance score, whilst others are said to use the level of the spouse who has the least preference for risk. Gilliam *et al* (2008: 10) suggested the use of the second method may be more effective as "the nature of risk tolerance [is] rooted in the psychological and emotional comfort of the client…" and therefore, to ensure that as a couple, the clients are comfortable the less tolerable partner should be considered. To overcome this the authors proposed that a couples' risk assessment tool be researched, where the overall score is calculated and weighted in the favour of the spouse with the lowest risk tolerance (Gilliam *et al*, 2008: 10).

In the study by Riley and Chow (1992: 34), discussed in 3.1.2.2, they found that individuals who had never been married were the least risk averse according to their RRAI. Those who had never married were followed by those who were married, divorced and widowed, whilst respondents classified as being separated were the most risk averse (Riley and Chow, 1992: 36). Yao *et al* (2005: 56), also discussed in more detail in section 3.2.1.2, found that married females preferred lower levels of risk when compared to similar married men, whilst single males were more willing to take on high and substantial levels of risk compared to married males.

Hartog *et al* (2000: 10 and 12), see section 3.2.1.3 for more detail, found that there was no relationship between marital status and risk tolerance in the Brabant Survey and the Accountants Survey, they did, however, consistent with most other studies, find with the GPD Survey that individuals who were married were more risk averse (Hartog *et al*, 2000: 15). From the simple model estimated by Christiansen *et al* (2009: 7), discussed in 3.2.1.3, it was concluded that married men had a higher probability of holding stocks than married women, whereas, when considering the bond market it was found that single individuals, rather than married individuals, were more likely to be investors. Married men were more likely to invest in bonds than married women as well. The findings from the extended model were also very similar to those in the simple model (Christansen *et al*, 2009: 7).

Generally, previous research seems to suggest that single individuals are more risk tolerant than married individuals. However, there is some evidence to suggest that this is not always the case and further research is needed, such as the finding by Hawley and Fujii (1994: 202), who found that, for females, married respondents were the most risk tolerant.

3.2.1.6 Education

It is generally believed that the level of education attained by an investor has a positive relationship with their risk tolerance levels (i.e. the higher the attained educational level of the investor the more risk they are willing to take). Gumede (2009: 6) mentioned that a factor that may contribute to this is that generally one's education level has a direct impact on one's earning power, typically the more qualified an individual was the better his/her chances of a higher employment status and thus, earning power or income. There is also a case that an improved education, ignoring any income or wealth effects, has a positive relationship with risk tolerance levels. This was the result found by Hartog *et al* (2000: 11), whose study found that "schooling level significantly reduces risk aversion, in particular for university education relative to lower levels…" The authors further indicated that income and wealth were both included in their regression model and thus, these variables were controlled for. Therefore, it follows that the lower risk aversion levels are independently linked to an increased level of education (Hartog *et al*, 2000: 11).

Riley and Chow (1992: 34), discussed previously in 3.2.1.2, also found that risk aversion declined as education levels improved but commented that education, income and wealth were highly correlated and thus, were unsure of whether it was a wealth effect or it could be attributed to education. More support for the existence of a positive relationship between education and risk tolerance was found by Schooley and Worden (1996: 93) (see 3.2.1.1). In their study Schooley and Worden (1996: 92) divided respondents into four education groups which were no high school diploma, high school diploma, some college and college degrees. The results from their univariate analysis concluded that the ratio of risky assets per dollar of wealth increased with an increase in the education level of the head of each household (Schooley and Worden, 1996: 93). In the same order of the groups listed above, the mean ratios of risky assets to wealth for each of the four were 0.608, 0.824, 0.870 and 0.904 (Schooley and Worden, 1996: 92). The authors did acknowledge that there may be a link to a human capital effect where a higher education was generally associated with higher earning power but that it may also be attributed to the fact that, a household that was more academically qualified could make more financially sophisticated investment decisions which were more risky (Schooley and Worden, 1996: 93).

Similarly, Sung and Hanna (1996: 14) found that after controlling for other variables, risk aversion decreases with an increase in education. In the study by Sung and Hanna (1996: 11) the research problem was to "…investigate effects of financial variables and individual characteristics on risk tolerance…" In order to do this they used a sample obtained from the 1992 SCF survey. In total there were 2 659 respondents who satisfied the criterion of being employed, aged between 16 and 70 years and having a positive non-investment income (Sung and Hanna, 1996: 12).

Like many other studies, Sung and Hanna (1996: 12) assessed respondents' risk tolerance levels by using the SCF risk tolerance question as the dependent variable in their model. It was reasoned that due to the substantial risk category being so small in their study it was not suitable for analysis, particularly with respect to variables such as education, race, age and income. Based on this they decided to combine the substantial and above average risk category in order to allow for a more meaningful multivariate analysis (Sung and Hanna, 1996: 12). Included among the independent variables was a dummy variable for education, amongst other dummy variables such as age, household size, race, marital status and gender (Sung and Hanna, 1996: 13). The categories defined for the education dummy variable were that of a respondent being a high school graduate (the base category), attaining an education level of less than high school, some college, or the final category of a Bachelor's degree or more. As per the normal treatment of dummy variables, if a respondent fell into one of the categories it would take on a value of one otherwise it would be zero. If the respondent was a high school graduate then, being the base category, the other three categories would all take on values of zero (Sung and Hanna, 1996: 18).

Extensive analysis of the data was conducted firstly by using Chi-square statistics "…to test for significant bivariate risk tolerance differences in sets of variables" (Sung and Hanna, 1996: 13). A logit model was then also used in order to test the effects that the explanatory variables had on risk tolerance (Sung and Hanna, 1996: 13). The Chi-square statistics showed that education was significantly related to risk tolerance. The logit regression results revealed that predicted risk tolerance increased with education, when the effects of other variables were controlled (Sung and Hanna, 1996: 14). Those respondents who had less than a high school education had a predicted risk tolerance of 43 percent, increasing to 54 percent for high school graduates, 62 percent for those with some college and 71 percent for those with a Bachelor's degree. The same positive relationship was evidenced for actual risk tolerance levels (Sung and Hanna, 1996: 14-15).

Based on the study by Sung and Hanna (1996: 14-15), there is evidence to support a positive relationship between risk tolerance and education, however, it is important to note that the authors acknowledged a potential weakness brought about by the use of the SCF risk tolerance question. In explaining this weakness, Sung and Hanna (1996: 17) recognise that this method is used fairly commonly in research of this nature, however, they advise that researchers should be cautious when interpreting its effects, as there appear to be both objective and subjective aspects to it.

In a study by Donkers *et al* (2001: 165), it was investigated whether risk attitudes changed with observed characteristics of individual respondents. In order to do this, a set of eight questions was used where the first five required the respondents to select one of two lotteries and the other three involved probability equivalence questions. In these three questions individuals were required to state the probability of winning a prize, where they were indifferent between receiving the lottery and receiving a given amount of money (Donkers *et al*, 2001: 166). According to Donkers *et al* (2001: 166), both sets of questions had an option considered to be risky, with high variance, and a safe option, with low or no variance, and they used this data to categorise individuals as more or less risk averse.

The data used in the study included 2 780 households, drawn from the CentER Savings Survey in 1993, that were divided into two panels. The authors reason that one of the panels was designed to be representative of the Dutch population, whilst the other was a random sample consisting of households who fell in the upper income distribution decile in the Netherlands (Donkers *et al*, 2001: 168). It was noted by Donkers *et al* (2001: 168) that respondents were not paid to participate in the survey as opposed to many other similar experiments but they state that there is evidence showing that there are no discrepancies in responses with and without monetary incentives given, at least in the simple case of using lotteries where there are two outcomes. The final, usable sample for estimation purposes consisted of 2 593 individuals after excluding responses where certain information was missing (Donkers *et al*, 2001: 170).

In analysing the data, Donkers *et al* (2001: 166) used both a semiparametric model and structural or parametric model. The semiparametric model was used to determine how an individual's appetite for risk was related to other characteristics. The structural model overcomes the weaknesses of the semiparametric model and allows for the analysis of an individual's decision processes. Cumulative prospect theory with unobserved heterogeneity and pure noise was used in the estimation of the structural model (Donkers *et al*, 2001: 166). The education variable in the models was treated as a dummy variable consisting of five categories which were not explicitly defined by

Donkers *et al* (2001: 172). Results from the semiparametric model suggested that education was significantly related to risk aversion levels (Donkers *et al*, 2001: 166 and 172). The results from the structural model were consistent with that of the semiparametric model in that education did have an effect on risk aversion (Donkers *et al* (2001: 166 and 185). The authors therefore, concluded that an investor's appetite for risk was positively related with his/her education level (Donkers *et al*, 2001: 185).

Grable and Joo (2004: 74) claimed that the determinants of financial risk tolerance can be classified into two groups. The first of these groups were biopsychosocial factors and included age, gender, race, birth order, self-esteem, personality, sensation seeking and financial satisfaction. The second group consisting of income, net worth, financial knowledge, home ownership, education and marital status were known as environmental factors (Grable and Joo, 2004: 74). In their study the authors aimed to improve the understanding of the determinants of financial risk tolerance as they were of the belief that "...financial risk-tolerance attitudes play a key role in the establishment of financial objectives and ultimately in the development of financial plans and strategies" (Grable and Joo, 2004: 74).

The specific purpose of the Grable and Joo (2004: 75) study was to test the effects of demographic, socioeconomic and psychosocial factors on risk tolerance levels of their sample. The sample consisted of 460 usable responses selected from "college faculty and staff" of two universities (Grable and Joo, 2004: 75). Financial risk tolerance, as the dependent variable used in the study, was measured using five Likert-type items from which scores were summated for the respondents. Higher scores translated into higher levels of financial risk tolerance (Grable and Joo, 2004: 75-76). Education, along with some of the other independent variables, was measured as a dummy variable taking a value of 1 for a respondent who was a college graduate (held a bachelor's degree at least) and 0 otherwise (Grable and Joo, 2004: 77). In order to test the relationship between the explanatory variables and financial risk tolerance, an OLS multiple regression analysis was used and the significance of the variables was tested using t-tests. Grable and Joo (2004: 78) also conducted tests for multicollinearity between variables, where it was found that education and occupational status had a high correlation and therefore, occupational status was omitted from the study.

The results from the regression analysis proved that the relationship between education and financial risk tolerance was statistically significant and positive (Grable and Joo, 2004: 78). This provided more support for the proposition that the more highly an individual was educated the greater was their risk tolerance. Grable and Joo (2004: 78), from their study, also suggested that environmental factors may be more critical in determining risk tolerance levels as opposed to originally thought. This was based on the fact that only one of the environmental factors investigated in the study, home ownership, was not significantly related to financial risk tolerance. These findings implied that environmental factors had more of a direct influence on risk appetites than biopsychosocial factors (Grable and Joo, 2004: 79).

The study by Bellante and Green (2004: 280), discussed in more detail in section 3.2.1.2, found evidence that education level attained had a significant effect on portfolio allocation. They concluded that individuals in their study who possessed a college degree were more risk tolerant than those who had graduated from high school, who, in turn, were more risk tolerant than those who had not (Bellante and Green, 2004: 277). These findings therefore, also maintained that there was a positive relationship between risk tolerance and education and Bellante and Green (2004: 277) further stated that differences in education levels accounted for larger differences in asset allocation compared to any other variable they examined.

Chang *et al* (2004: 56) investigated, as part of their study, whether households with heads that were more educated had higher levels of risk tolerance than those who were less educated. Part of this hypothesis was to also test whether the same results were found using both a subjective and an objective measure of risk tolerance. The authors used the 2001 SCF for their sample which consisted of 4 442 households (Chang *et al*, 2004: 57). Objective risk tolerance was measured as the ratio of risky assets to net worth, whilst subjective risk tolerance was measured using the SCF risk tolerance question (Chang *et al*, 2004: 57). In order to model the effects that individual characteristics had on the two measures, an OLS regression was used when subjective risk tolerance was the dependent variable. In the case of the dependent variable being objective risk tolerance, a Tobit regression was used (Chang *et al*, 2004: 59). Furthermore, a Chi-square analysis was used to examine the relationship between education, amongst other variables, and subjective risk tolerance (Chang *et al*, 2004: 59).

The educational categories used by Chang *et al* (2004: 61) were high school or less, some college, college degree and graduate school. The findings from the Chi-square analysis were that households, represented by a head with a high school or less education, were the most likely to select no tolerance for risk and that an increase in education level corresponded to an increase in risk tolerance (Chang *et al*, 2004: 62). The OLS results implied that education was a significant predictor of subjective risk tolerance and that respondents with higher education levels were more likely to exhibit a positive relationship with subjective risk tolerance (Chang *et al*, 2004: 62-64). When studying objective risk tolerance it was concluded that the ratio of risky assets to net worth was higher for respondents in the higher educational categories (Chang *et al*, 2004: 64). This result was consistent with the findings related to subjective risk tolerance and it could be argued that this is expected, as Chang *et al* (2004: 64) also found that subjective risk tolerance was positively related to objective risk tolerance.

Importantly, Chang *et al* (2004: 65) concluded that financial advisors should be cognisant of the educational backgrounds of their clients when giving advice. This is due to the fact that clients with lower qualifications may need more information when making investment decisions. Chang *et al* (2004: 65) also stated that because education was such an important factor affecting risk tolerance, financial advisors need to carefully consider the advice they provide when explaining risk tolerance and must avoid making assumptions based on an individual's demographics.

Yao *et al* (2005: 56), see section 3.2.1.2 for more detail on this study, inferred that education, which was linked to familiarity with financial markets, had no significant effect when considering the substantial risk tolerance category. On the contrary, however, there was indeed a positive relationship (with education) with having a high level of financial risk tolerance and some financial risk tolerance. Kimball, Sahm and Shapiro (2007: 1) developed a quantitative proxy for risk tolerance which was derived from responses to hypothetical questions by participants in their sample of 11 616 individuals (Kimball *et al*, 2007: 9). The risk tolerance proxy developed by Kimball *et* *al* (2007: 20) was able to explain household asset allocation differences and concluded that "...the most educated are more risk tolerant."

Based on the studies reviewed here, there seems to be overwhelming support for a positive relationship between risk tolerance and education. There is, however, the possibility that education is merely a proxy for income and that effects may be income-linked rather than educational. The use of a statistical model which controls for the interaction of other variables in analysing a relationship is, therefore, very important and will be used in this study.

3.2.1.7 Religion

The literature on the variable religion and its effect on risk tolerance appears to be very limited, possibly due to the sensitivity of the issue, however, studies such as those conducted by Barsky *et al* (1997), Halek and Eisenhauer (2001) and Hartog, Ferrer-i-Carbonell and Jonker (2002) have investigated this relationship.

Barsky *et al*'s (1997: 537) study presented measures of risk tolerance, time preference and intertemporal substitution based on preference parameters derived from responses to a survey of hypothetical scenarios. The authors acknowledged that although using surveys does introduce certain problems, such as the accuracy of responses, it may also be used as an important source of information along with econometric evidence (Barsky *et al*, 1997: 538). In the study, risk aversion measures were obtained from individual's responses pertaining to their willingness to gamble on lifetime income (Barsky *et al*, 1997: 538). In their methodology, Barsky *et al* (1997: 539) stated that, "[t]he principal requirement for the question aimed at measuring risk aversion is that it must involve gambles over lifetime income." After conducting various tests the following questions were asked as part of the study (Barsky *et al*, 1997: 540):

> "Suppose that you are the only income earner in the family, and you have a good job guaranteed to give you your current (family) income every year for life. You are given the opportunity to take a new and equally good job, with a 50-50 chance it will double your (family) income and a 50-50 chance that it will cut your (family) income by a third. Would you take the new job?"

If the response to this question was "yes", then the following question was asked:

> "Suppose the chances were 50-50 that it would double your (family) income, and 50-50 that it would cut it in half. Would you still take the new job?"

However, if the answer to the first question was "no", then the following question was asked:

> "Suppose the chances were 50-50 that it would double your (family) income, and 50-50 that it would cut it by 20 percent. Would you then take the new job?"

Classification into risk tolerance categories was dependent on the answers obtained for each respondent. Category I (the least risk tolerant) consisted of those individuals who rejected both gambles. Category II included those who rejected the one third gamble but accepted the one fifth gamble. Category III was reserved for those who accepted the one third gamble but rejected the one half gamble and category IV (the most risk tolerant) included individuals who accepted both gambles (Barsky *et al*, 1997: 541).

According to Barsky *et al* (1997: 544), the questions were included in Wave I of the 1992 HRS with respondents between the ages of 51 and 61 being targeted. In total 11 707 responses were elicited. Barsky *et al* (1997: 549) divided respondents into four religious groups being that of Protestant, Catholic, Jewish and other. Results from the study yielded the following with respect to Protestants: 66.2 percent fell into risk tolerance category I; 11.5 percent in category II; 10.8 percent in category III, and 11.4 percent in category IV. For Catholic respondents the respective ordering was 62.3 percent, 10.8 percent, 11.4 percent and 15.3 percent. Jews had an allocation, in the respective order, of 56.3 percent, 13.2 percent, 11.1 percent and 19.2 percent whilst for the "other" group it was 61.6 percent, 14.3 percent, 9.6 percent and 14.3 percent respectively (Barsky *et al*, 1997: 549). One can see from these results that in all four religious groups the majority of respondents fell into category I and therefore, were considered to be the most risk averse. These results are, however, very inconclusive and are not comparable across the different groups and therefore, the mean risk tolerance scores were more applicable. The mean risk tolerance scores were calculated using the baseline parametric model (Barsky *et al*, 1997: 549). Analysing these scores showed that risk tolerance varies significantly according to religion with Protestants appearing to be the least risk tolerant (0.2350). Catholics (0.2514) were more risk tolerant than Protestants, however, Jews (0.2683) were found to be the most risk tolerant (Barsky *et al*, 1997: 549). It can thus, be suggested that religion does impact attitudes towards financial risk based on the study of Barsky *et al* (1997: 549).

The study by Halek and Eisenhauer (2001: 2) provided new insight, at the time, as to how RRA was impacted across demographic categories. Those categories examined were age, gender, education, nationality, race, marital status, parental status, health and behavioural indicators, employment status, income and wealth and religion. The authors aimed to extend on previous research of a similar nature and stated that this would be achieved by building on the three typical approaches involved (Halek and Eisenhauer, 2001: 1). In the authors' own words the first approach included the derivation of "…a reduced form equation for the Pratt-Arrow measure of relative risk aversion without imposing prior assumptions on the shape of the utility function" (Halek and Eisenhauer, 2001: 1). Their reasoning for this was that some of the previous research conducted on RRA and its relationship with demographic factors had assumed utility functions that showed CRRA behaviour and therefore, proscribing any tests of the IRRA hypothesis.

The second step was to then estimate individual household risk aversion parameters empirically and this was done using data on life insurance purchases (Halek and Eisenhauer, 2001: 1-2). From the particular data set used, over 2 300 Arrow-Pratt measures were then calculated and these were, subsequently, used to analyse the relationship between RRA and the demographic variables already listed above. The explanation justifying this step was that many studies have inferred RRA measures, rather than calculating them, and this has been based on either the method of asking hypothetical questions or alternatively, gamble scenarios (Halek and Eisenhauer, 2001: 1). The final step of the research allowed Halek and Eisenhauer (2001: 2) to examine behaviour towards employment and income risk by studying responses to a hypothetical question.

The particular model, after various mathematical manipulations, used to measure RRA is shown as follows (Halek and Eisenhauer, 2001: 6):

$$R(E[W]) \equiv -E[W]U''(E[W])/U'(E[W]) = E[W]\theta/(Y-V^*) \tag{3-3}$$

Where: V = life insurance coverage available at a premium rate;

Y - V* = the uninsured portion of potential loss; and,

θ = the relationship between the loading factor (λ) and the probability of survival (1 – p).

The sample employed by Halek and Eisenhauer (2001: 6) was extracted from the 1992 survey data from Wave I of the University of Michigan HRS study, similar to Barsky *et al* (1997), and consisted of 12 652 individuals from 7 607 households. The households included in the study were those who had bought life term insurance on the primary respondent who was considered the head of the household. V* in the model shown above was said to be the total face value of all term insurance policies on the household head and Y the potential loss experienced by the household upon the death of the head (Halek and Eisenhauer, 2001: 6). Mortality rates (p in the model above) were also calculated for every primary respondent, whilst assets (denoted A in their study) measured net worth and included housing (Halek and Eisenhauer, 2001: 7).

Halek and Eisenhauer (2001: 7) included two examples showing how, according to their calculations, risk aversion measures were calculated for two potential respondents. This was very helpful for the reader and the examples are reproduced here. The first respondent, who was a married Hispanic male, aged 52 years old, with $113 000 worth of assets (A), $504 968.50 in human capital (Y) and life term insurance (V*) of $278 000. With an age-based mortality rate (p) of 0.007655 and a premium rate (denoted m) of 0.00932 the values of λ, θ and E[W] were calculated to be 1.2175, 0.21918 and $613 640.10 respectively. Using equation 3-3, the Arrow-Pratt risk aversion measure (R(E[W])) was calculated to be 0.5926. The second example was of a respondent who was an unmarried White female parent, 58 years old, with assets equal to $101 000, insurance of $56 000, human capital of $93 990.78, a mortality rate of 0.007397 and a premium rate of 0.009405. In this case λ was equal to 1.27146, θ to 0.27348, E[W] to $194 183.08 and R(E[W]) was 1.398. This represented a RRA measure more than double that of the individual in the first example (Halek and Eisenhauer, 2001: 7).

Using the model discussed above and the RRA parameters calculated for the respondents, a multivariate regression analysis was then used to analyse the impact of the demographic variables on risk aversion levels (Halek and Eisenhauer, 2001: 7). In particular the religious denominations of Protestants, Catholics and Jewish investors were examined and it was found that an investor's religious belief had a minimal effect on the level of risk aversion of that investor (Halek and Eisenhauer, 2001: 13). However, after applying a process referred to as backward elimination to the two semi-log models estimated it was found that the coefficient of Catholic was significant but only in the first model. This suggested that if a respondent was Catholic their level of risk aversion would only experience a slight increase of 6.65 percent in comparison to the other groups, which had no significant effect (Halek and Eisenhauer, 2001: 13).

Halek and Eisenhauer (2001: 14) also ran a full-log regression as part of their study, which according to their results had more explanatory power, and found slightly different results to those in the semi-log models. It was concluded that being Jewish was the only variable that impacted on risk aversion and in this case risk aversion increased by 20.97 percent for a Jewish respondent (Halek and Eisenhauer, 2001: 14). Their final conclusion from their study was that "…it appears likely that differences in religious beliefs affected attitudes toward risk taking, rather than [*vice versa*]" (Halek and Eisenhauer, 2001: 22).

Hartog *et al*'s (2002: 16) study, an extension to their 2000 study (discussed in detail in section 3.2.1.3) and therefore, very similar in all aspects, found that "…frequent church visits (forty times or more per year) correlate[d] with higher risk aversion." Reasons they attributed to this, included that religious people may be more prudent and that in some cases, due to moral objections to gambling, religious respondents indicated a reservation price of zero for the lottery based scenario [already explained in section 3.2.1.3 as part of Hartog *et al*'s (2000) study] (Hartog *et al*, 2002: 16). From the studies examining the correlation between religion and risk tolerance it can be seen that there was some evidence supporting the possibility of a significant relationship. There was no clear link though between belonging to a certain religious denomination and being more or less risk tolerant than another and therefore, more research is justified.

The table which can be found in Appendix A serves as a summary of the studies reviewed in this section.

A discussion of the two South African studies reviewed in this field of literature follows in the next section.

3.2.2 South African Studies

As previously mentioned there have been South African studies in the Agricultural Economics field which have focused on assessing risk aversion, however, the literature in Economics and Finance is very limited. The following review of literature identifies two such studies which investigated the relationship between demographic factors and financial risk tolerance.

3.2.2.1 Strydom, Christison and Gokul (2009)

The first South African study was compiled by Strydom *et al* (2009: 1) with the purpose of using an existing risk tolerance measure to determine whether certain demographic factors impacted on the risk tolerance levels of a sample, from a South African perspective. The four demographic variables investigated in this study were gender, race, religion and income and formed part of the hypotheses listed by Strydom *et al* (2009: 6). In order to assess individuals' risk tolerance levels a survey approach was used and a total of 84 third and fourth year Accounting and Finance students from the University of KwaZulu-Natal's (UKZN) Pietermaritzburg campus participated (Strydom *et al*, 2009: 6). One of the reasons that this particular sample was used was that an intention of the study was to make it comparable to the Hanna and Lindamood (2004) study, which also used a sample of university students, and to determine whether there was any difference in the results across the two studies.

The particular survey approach used, a subjective risk tolerance measure, was adapted from the Hanna and Lindamood (2004) study and included a pension risk question as well as a second measure where respondents were required to choose one of seven hypothetical portfolios which best suited their desired investment mix (Strydom *et al*, 2009: 7). The portfolios had proportional allocations in securities that were classified as either high risk/high return, medium risk/medium return or low risk/low return (Strydom *et al*, 2009: 7-8). The portfolios are outlined as follows:

<u>Table 3-1:</u> Hypothetical Portfolios

Portfolio	High Risk/Return	Medium Risk/Return	Low Risk/Return
1.	0%	0%	100%
2.	0%	30%	70%
3.	10%	40%	50%
4.	30%	40%	30%
5.	50%	40%	10%
6.	70%	30%	0%
7.	100%	0%	0%

Source: Strydom *et al* (2009: 8)

The second risk tolerance measure, used for comparison purposes, was taken from the studies by Faff *et al* (2004: 10) and Subedar *et al* (2006: 18) (Strydom *et al*, 2009: 7-8). Strydom *et al* (2009: 8) supported the use of including this measure in the questionnaire as they claimed it was an ideal way to categorise individuals into their relevant risk tolerance levels. This was evident when examining the table above as portfolio 1 is obviously the portfolio with the least amount of risk, whilst portfolio 7 has the most risk (Strydom *et al*, 2009: 10). Each portfolio was then ranked according to a risk tolerance level which was determined by applying utility theory to the pension risk question and calculating a RRA value (Strydom *et al*, 2009: 9). The categories of risk tolerance and their inverse (risk aversion levels) identified by Strydom *et al* (2009: 9) are shown below with their corresponding portfolio:

<u>Table 3-2:</u> Risk Tolerance (Risk Aversion) Level and Corresponding Portfolios

Risk Tolerance Level	Risk Aversion Level	Corresponding Portfolio
Ext. High Risk Tolerance	Ext. Low Risk Aversion	7.
Very High Risk Tolerance	Very Low Risk Aversion	6.
High Risk Tolerance	Low Risk Aversion	5.
Moderate Risk Tolerance	Moderate Risk Aversion	4.
Low Risk Tolerance	High Risk Aversion	3.
Very Low Risk Tolerance	Very High Risk Aversion	2.
Ext. Low Risk Tolerance	Ext. High Risk Aversion	1.

Source: Adapted from Strydom *et al* (2009: 8-9)

The data in the study was analysed using nonparametric techniques with the hypotheses tested by using the Chi-Squared (χ^2) Test; Kendall's tau statistic; Spearman's rho; the Mann-Whitney U test and the Kruskal-Wallis test (Strydom *et al*, 2009: 10). The results from the study are discussed below.

With regards to gender, Strydom *et al* (2009: 15) found, in their study, that more males were grouped into the very high and extremely high risk tolerance categories with more females falling in the very low and moderate risk categories. It must be noted, however, that the Mann-Whitney test statistic for the first measure "Hanna and Lindamood (2004)" was not significant, whilst it was significant for the second measure, referred to as the SCF measure by Strydom *et al* (2009: 15). The authors further stated that that the differences could not be attributed to exposure to financial knowledge as all respondents were in the same Accounting and Finance classes and therefore, had received the same level of education (Strydom *et al*, 2009: 16).

Strydom *et al* (2009: 16) performed a Chi-squared test on the findings from the Hanna and Lindamood (2004) measure and found that there were significant differences in risk tolerance across the racial groups included in the study. Mann-Whitney tests showed that there was a significant difference between Whites and Indians as well as Whites and Blacks when considering financial risk tolerance (Strydom *et al*, 2009: 17).

Strydom *et al* (2009: 17), in investigating the effects religion had on risk tolerance, excluded the Jewish category from their study as there were no respondents of this nature. This left the three categories of Christian, Hindu and Muslim. Tests conducted by Strydom *et al* (2009: 18) found that Christians were the least risk tolerant compared to Muslims and Hindus respectively. It was concluded that there was a significant difference between the risk tolerance of Christians and Hindus, however, Strydom *et al* (2009: 18) cautioned that one would need to control for race in their sample as they found "...a major overlap [existed] between the racial and religious classifications." Of the 56 Christian respondents, 23 were White, whilst all the Hindu respondents were Indian illustrating the difficulty in determining whether differences in risk preferences may be due to either racial or religious classifications (Strydom *et al*, 2009: 18).

When investigating the variable income, the results from the study by Strydom *et al* (2009: 18) suggested that there was no significant relationship between income and risk tolerance. However, Strydom *et al* (2009: 19) acknowledged that limitations in their sample made this finding questionable as, firstly, there was a poor response to the income question (a 48% response rate) and, secondly, the students were required to estimate their household incomes (including their parents' incomes) and these were deemed to possibly be inaccurate. Another issue was that the sample may be biased as "...there is a greater likelihood that respondents from wealthier families are more likely ... to attend university" (Strydom *et al*, 2009: 19).

The correlation between the two measures used by Strydom *et al* (2009: 12) was also tested in order to determine whether framing had any impact on responses. Results showed that there was a low correlation for the male participants and none for the females between the two measures and this suggested that framing did in fact impact responses (Strydom *et al*, 2009: 14). The study by Strydom *et al* (2009) did not account for the effects of education level, marital status and age on risk tolerance. The study by Gumede (2009), which also included the same variables as the Strydom *et al* (2009) study, and introduced further variables, is discussed next.

3.2.2.2 Gumede (2009)

The second South African study was conducted by Gumede (2009: 4) where the author aimed to improve on the limitations of the Strydom *et al* (2009) study in investigating how demographic factors influenced appetites for financial risk. Gumede (2009: 17) used a more diverse sample of first year Economics students from the UKZN Pietermaritzburg campus and investigated the variables; gender, race, religion, economic expectations, education, income and knowledge of personal finance. The survey instrument employed in this study followed the instrument used by Strydom *et al* (2009) (Gumede, 2009: 18).

Gumede (2009: 4 and 17) used a technique known as the ordered dependent variable (odv) method to analyse the data collected in the study, which served to isolate the impact that demographics had on an individual's level of risk tolerance. Results from the Gumede (2009) study are discussed next.

The study by Gumede (2009: 22 and 33) found that there was no significant relationship between gender and subjective or investment financial risk tolerance. This was contrary to the majority of studies who have investigated this relationship as shown in section 3.2.1.4. Gumede (2009: 24 and 34) found that, for the relationships between both subjective risk tolerance and race and investment risk tolerance and race, Whites had a greater propensity for a higher level of financial risk compared to the other race categories (Blacks, Asians/Indians and Coloureds). The effect of race was found to be marginally significant for Blacks, Whites and Asians/Indians (Gumede, 2009: 24 and 34). When analysing the correlation between income and risk tolerance, Gumede (2009: 28 and 37) found that there was indeed a positive link between risk tolerance, both subjective and investment, and an investor's income bracket. The odv regression findings, however, contradicted this as it was found that the income variable was not a significant determinant of risk tolerance (Gumede, 2009: 28-29 and 38).

Gumede (2009: 28) found that an individual's subjective risk tolerance was affected by the level, or quality, of education received. His finding was that the respondents who attended a model C school as opposed to a government school were more likely to have a higher tolerance for financial risk. It must be noted that there was no support for a significant relationship between the two variables and the results were merely suggestive (Gumede, 2009: 27). With regards to investment risk tolerance, it was found that the relationship with education was not significant (Gumede, 2009: 37). In contrast to Strydom *et al* (2009: 18), Gumede (2009: 26) found that religion had no significant effect on the level of subjective risk tolerance borne by an individual, however, he found that Christians were more risk tolerant than Hindus in the case of investment risk tolerance (Gumede, 2009: 35). Gumede (2009) did not investigate the relationships between marital status and risk tolerance and age and risk tolerance.

Table A-1 in Appendix A includes a summary of the two South African studies.

The following discussion outlines the limitations of the two South African studies.

3.2.2.3 Limitations of the South African Studies

Whilst the two studies discussed above have made important contributions to a topic that has received little focus from a South African perspective there are, however, some limitations and weaknesses evident in the respective studies.

Firstly, the sampling techniques of both were limited to UKZN students which resulted in a largely homogenous set of respondents rather than a more representative sample. Furthermore, the samples were fairly small in size. Unfortunately, due to the problems in the sampling process, the studies by Strydom *et al* (2009) and Gumede (2009) could not investigate the relationship between marital status and risk tolerance as well as age and risk tolerance. This may be attributed to the homogeneity found amongst their respective samples of students at the UKZN. As mentioned previously, Strydom *et al* (2009: 19) also experienced difficulties in analysing the relationship between income and risk tolerance and this variable had to be omitted from their analysis.

The second weakness of the studies is that the different statistical analysis techniques did not allow for a more robust analysis and this is particularly evident in the Strydom *et al* (2009) study. The authors chose to use nonparametric techniques in their study as well as conduct median analyses of the data groups (Strydom *et al*, 2009: 10). By their own admission it was noted that the significance of the results, most notably when analysing the variables race and religion, was not easy to interpret due to overlaps in the categories and the inability to control for the effects of other variables (Strydom *et al*, 2009: 18).

Finally, it can be construed that the questionnaires used in the aforementioned studies were not suitable for the purposes of this study. The Strydom *et al* (2009) study used a variation of the pension scenario questionnaire from the Hanna and Lindamood (2004) study, however, it could be argued that this particular questionnaire, due to the intricacies of the questions, is more suitable to respondents with a certain level of economic or financial knowledge. This was generally the case in the Strydom *et al* (2009) study as the UKZN student sample would have been largely homogenous with respect to education. A further limitation of the questionnaire in concern was that it only measured the concept of financial risk tolerance in terms of income risk where, in fact, financial risk could be viewed as a much broader term covering a group of risk categories including speculative risk, investment risk and guaranteed versus probable gambles amongst others. This was explored in a study by Grable and Lytton (1999a) who concentrated on the development and analytical testing of a risk assessment tool or questionnaire as an improved means of measuring risk tolerance. A questionnaire which is designed to measure a variety of different risk categories could improve the analysis of an individual's risk tolerance. The two questionnaires mentioned here are discussed further in chapter four as part of the methodology of this study.

In summary of all the studies reviewed there are some major themes which are evident. First, and probably most importantly, there was overwhelming support that certain demographic factors influence individual financial risk tolerance. One of these was the age of an investor where it appears that risk tolerance is inversely related to age. There is no obvious link between race and risk tolerance, whilst it appears that males are generally more risk tolerant than females. The majority of studies which investigated the relationship between income and risk tolerance suggested there exists a positive relationship between the two which is also the same for the relationship between education and risk tolerance. Marital status was also found to affect risk tolerance, where single respondents were generally the most risk tolerant in the various studies. Studies on the impact religion had on risk tolerance have not been as numerous as those investigating the other variables but it was suggested that it can be linked to changes in risk tolerance levels. It was also evident that a variety of different methods were used when measuring or assessing risk tolerance levels and this proves that there is no one specific method applied. It appears that researchers select the most appropriate technique for their studies given various parameters and constraints. It is important to keep these main themes in mind as one reads further in this study into the relationship between risk tolerance and demographic variables.

4 METHODOLOGY

4.1 Problem Statement and Objectives

Based on the preceding literature review it is evident that assessing a person's risk tolerance is an important issue in investment finance and that an individual's social and demographic characteristics have an influence on the asset allocation decision. Understanding how these characteristics impact on one's risk tolerance or alternatively, risk aversion levels is therefore, an important research question. As such the purpose of this paper was to determine to what extent demographic factors influenced an individual's subjective financial risk tolerance level. Research on this subject is very limited in the South African context, however, the aforementioned Strydom *et al* (2009) and Gumede (2009) papers are two studies which have attempted to address this topic but their analysis was limited in its application as they made use of student samples. Therefore, a larger and more representative sample was sought in this study in order to address the sample limitations of the two South African studies examined.

Support for the purpose of this research was provided by the fact that a number of international studies, such as Bellante and Green (2004: 277); Jianakoplos and Bernasek (2006: 999); Sahm (2007: 29) and Christiansen *et al* (2009: 8), have found that demographic factors do in fact influence an individual's risk tolerance levels. As such, the demographic factors that were investigated, as per the literature review, are listed as follows: age, gender, education, marital status, race, income and religion and are summarised by the following research objectives:

- To determine whether age affected individual subjective risk tolerance
- To determine whether there was any difference in individual subjective risk tolerance levels for males and females
- To determine whether education level affected individual subjective risk tolerance levels
- To determine whether marital status had any effect on individual subjective risk tolerance levels
- To determine whether race affected individual subjective risk tolerance levels

- To determine whether income affected an individual's subjective risk tolerance level
- To determine whether religion affected individual subjective risk tolerance levels

To address these research objectives a study sample was needed in order to conduct the necessary statistical tests upon the data collected in the sample process. The following section details this process.

4.2 Sample

4.2.1 Population

According to Walliman (2005: 275), research by means of a survey is heavily dependent on the sampling process and the asking of questions, using questionnaires, interviews or observations. The aspect of the statement which refers to the asking of questions using a questionnaire is detailed in section 4.3, whilst the focus here is on the study sample. Another important issue to consider is the representivity of the sample, relative to the population, used in the study. Walliman (2005: 276) refers to the population as "...a collective term used to describe the total quantity of cases of the type which are the subject of your study..." and Alreck and Settle (1995: 54) stated that the first step in designing a sample is to define the population. The population for this study was therefore, defined as all those people within the city of Pietermaritzburg, over the age of 17, who visited the shopping malls used at the time that the survey process took place. As it was not feasible to survey the whole city a sample of respondents was selected. How representative a sample is of the population is directly linked to the validity of the method of randomisation used in its selection (Leedy, 1989: 153). The randomness of a sample is, however, dependent on which of the two main sampling techniques (nonprobability or probability) is used with the random methods being part of the probability sampling group (Leedy, 1989: 153). Therefore, by using a nonprobability technique the representivity of the sample is potentially compromised as there is not a great deal of random selection that takes place. Results from a non-random sample are generally not representative of the whole study population but important inferences can be made from their results (Walliman, 2005: 276).

4.2.2 Sample Design

4.2.2.1 Sampling Technique

The Strydom *et al* (2009: 6) study used a sample of third and fourth year Accounting and Finance students from the UKZN Pietermaritzburg campus. As a result the respondents could be regarded as generally homogenous in factors such as age, education and their income earning status and therefore, a more diverse and larger sample without the same homogeneity was sought in this study. In order to achieve a more varied and larger sample, a survey was conducted at a variety of shopping malls around Pietermaritzburg to increase the possibility of achieving the said sample. The town of Pietermaritzburg was used in the study for two main reasons. Firstly, it was geographically accessible for the required research purposes and secondly, it allowed for the sampling of a diverse range of respondents specifically with respect to the large Indian population comprising Christian, Hindu and Muslim members. The reason for the use of more than one shopping centre or mall was to account for the fact that certain malls were located in more affluent areas as opposed to those in less affluent areas of the city, some were in areas where residents were predominantly of one race or religion and so on. By doing this it was hoped that a wider and more diverse range of respondents would be reached and thus, a more relevant study would be conducted.

According to Hornik and Ellis (1988: 539), Sudman (1980: 423) and Bush and Hair (1985: 158) the mall intercept method of data collection is one of the most popular methods used in studies where interviews are included. One of the contributing factors behind the popularity of this method is that due to the rising costs of door-to-door interviews it is more cost effective for a researcher to be based in a central location (i.e. a shopping mall) and conduct face-to-face interviews (Bush and Hair, 1985: 158, Hornik and Ellis, 1988: 539 and Sudman, 1980: 423). Further advantages of the shopping mall survey technique, listed by Hornik and Ellis (1988: 539), are those of greater control of the interview process and increased flexibility in conducting various experiments. Sudman (1980: 423) reasons that costs are decreased as the interviewer is no longer required to travel as in the case of door-to-door interviews and the mall intercept method has the added advantage over telephonic interviews in that visual aids can be used.

Given the advantages of the mall intercept survey method there are some weaknesses in its approach which are also important to acknowledge. Hornik and Ellis (1988: 539) stated that this survey technique is "...vulnerable to haphazard sampling procedures and high nonresponse rates, with the attendant problem of possible survey bias." Sudman (1980: 423) also mentioned that when conducting mall intercept surveys samples are selected haphazardly and therefore, are not representative of the general population. Whilst, Bush and Hair (1985: 159) claimed that a face-to-face mall intercept interview may help in collecting more sensitive information and receiving more in-depth responses compared to a telephonic interview, however, due to a social desirability effect the results may be more distorted.

Bush and Hair's (1985) study investigated various hypotheses in order to determine whether there were any differences between the mall intercept method and that of telephonic interviews. The dependent variables introduced in the study were that of completeness of answer, response distortion, validation of responses, item omission, response rates, shopping behaviour and lifestyles (Bush and Hair, 1985: 162-165). With regards to completeness of answer it was found that there was no significant difference between the two methods, however, the findings for response distortion proved to be particularly interesting (Bush and Hair, 1985: 162). Using Chi-square statistics the authors found that contrary to their original beliefs the respondents in the telephonic interviews gave the more socially desirable answers and there was a significant difference between the mall intercept method and the telephone method (Bush and Hair, 1985: 162). The findings from the other categories were that the two methods were generally quite similar, however, Bush and Hair (1985, 163) stated that according to their study the mall intercept method provided more accurate, or less distorted, responses.

Sudman (1980: 425) discussed the issue of choosing the location of where respondents are to be approached when using shopping mall intercepts. Simply, one can either select respondents as they arrive at the entrances or whilst they are moving around in the mall. Sudman (1980: 425) believes that the better approach is to use the entrances as the use of a survey of people already within the mall results in individuals who spend more time in the mall having a higher likelihood of being selected. Furthermore, if a shopping mall has more than one entrance it is necessary to use all of them as "[a]n unbiased sample requires that all entrances have some probability of selection" (Sudman, 1980: 425).

In the event where a mall only had one entrance, obviously, no other entrances were used in the sampling process. Where there was more than one entrance the decision had to be based on convenience taking into account the concerns of the mall managers. Over and above the issue of the location it was also important to consider the impact of time sampling (Sudman, 1980: 426). The reason for this is that different people, shop at different times, on different days of the week and this is obviously also affected by the time of the month as well as the year. Therefore, it was important to take these issues into consideration and thus, choose times of the day and week in which the survey took place in order to approach and account for a more diverse range of respondents. It must be noted that unfortunately, due to time constraints, different months of the year could not be included in the study. The survey was conducted over a period of a month (June) at three shopping malls in the Pietermaritzburg area. By surveying respondents on different days of the week and at different times of the month it was hoped that a more diverse sample was achieved. It must be noted that the days chosen for research purposes were conditional to approval from the relevant mall managers.

It is acknowledged that no surveys were conducted on weekends and therefore, it could be argued that the sample is biased towards people who do not work. However, a question requesting respondents to indicate their employment status was included in the questionnaire in order to address this issue (see Appendix B). The sample statistics obtained from this question showed that the majority, 204 of the 313 respondents who answered this question, were either employed or self-employed. This provides evidence that suggests no bias is present in the sample.

Although, the shopping mall survey method was used it was important to decide on which of the various sampling techniques available would be used in the study, as a means of selecting the respondents to be surveyed. According to Malhotra (1996: 364), McGown (1979: 194), Hair, Wolfinbarger, Ortinau and Bush (2008: 131) as well as de Vaus (1996: 60) there are essentially two main types of sampling techniques which are referred to as probability and nonprobability sampling, whilst Walliman (2005: 276) refers to them as random and non-random sampling respectively. The four most common methods of nonprobability sampling are convenience sampling, judgemental sampling, quota sampling and snowball sampling (Malhotra, 1996: 365). The techniques which fall in the category of probability sampling are those of simple random sampling, systematic sampling, stratified sampling and cluster sampling (McGown, 1979: 195). The distinguishing feature between the two main types of sampling is that in nonprobability sampling, chance selection processes are ignored in favour of personal judgement of the researcher, whereas, with probability sampling there is a fixed, non zero, probability that an element of a population may be chosen as part of a sample (Malhotra, 1996: 365 and Hair *et al*, 2008: 131). It is important to note that nonprobability sampling techniques may or may not be wholly representative of a certain population whilst, on the contrary, probability sampling allows a researcher to generalise results as being representative of the target population given a margin of sampling error (Hair *et al*, 2008: 131 and de Vaus, 1996: 60-61).

Given the nature of the explanatory variables, representing different strata of the population, one could argue that the sampling technique known as stratified random sampling, a probability technique, was the most appropriate method to have used. According to Hair *et al* (2008: 133), "[t]o ensure that the sample maintains the required precision, representative samples must be drawn from each of the smaller population groups (stratum)." Based on this it is evident that the use of such a sample would have required an extremely large sample size in order to bolster the reliability and representativeness of the results from the study. This is based on the fact that if one wanted to analyse the relationship between race and income and risk tolerance levels, for example, where there exist four and six categories respectively (see Appendix B), for these two categories alone one would need to find 180 respondents of each racial classification [based on a minimum number of 30 respondents in each income category (Leedy, 1989: 158)] and therefore, a total of 720 respondents alone would be needed for any meaningful analysis to be conducted on these two variables. The total sample size is multiplied even further if one considers that the study included seven explanatory variables. The ability to employ stratified random sampling was clearly inhibited by certain constraints such as time and cost and therefore, it was decided that in order to obtain a workable sample a different technique was necessary.

A more suitable sampling technique proved to be that of quota sampling, part of the nonprobability sampling technique family. This particular method was chosen so as to ensure that the preselected subgroups of the population were included or represented (Hair *et al*, 2008: 136). The selection of these subgroups forms part of what Malhotra (1996: 367) refers to as one of the two steps associated with quota sampling. The first step is to develop certain control categories, otherwise known as quotas, of the sample population. These control categories are selected based on the researcher's judgement and typically include factors such as sex, age and race (Malhotra, 1996: 367), making it the ideal method for this study. The second step is to then select the sample elements or respondents, as was the case in this study, based on convenience or judgement. It is for this reason that Malhotra (1996: 367) refers to this method as two-stage restricted judgemental sampling.

The advantages of using the quota sampling method include the fact that the correct subgroups are selected and included in the survey, the researcher has control over the proportions of the relevant subgroups and it is said to limit selection bias in the sampling process (Hair *et al*, 2008: 136). Sudman (1980: 430) also noted that the use of quota sampling reduces the sampling variance. Malhotra (1996: 368) claimed that this particular method of sampling has the advantages of lower costs and greater convenience for interviewers. Given these benefits, some authors do, however, highlight that the major drawback of a quota sample is that it is not always the most representative sample even if, for example, the sample composition is proportionate to that of the population according to the control variables or characteristics (Malhotra, 1996: 368; McGown, 1979: 205). Hair *et al* (2008: 136) acknowledged that due to the fact that the method in discussion is a nonprobability technique the representativeness of the sample cannot be measured and therefore, it is not recommended that results from the study be generalised to a wider population. However, important inferences as to certain relationships can be made. The study sample is discussed next.

4.2.2.2 Sample

As per the literature review, the subpopulations, which the control variables were selected from, for the purpose of this study, are listed as follows:

1. Age
2. Gender
3. Education
4. Marital Status
5. Race
6. Income
7. Religion

It is important to note, with reference to the control variable income, that although both income and wealth were reviewed in section 3.2.1.3 only income was measured in this study. As was discussed in section 3.2.1.3 the two factors are highly correlated and therefore, show similar effects on risk tolerance. Over and above this it is very difficult for respondents to accurately estimate their true wealth levels and it is very unlikely that consistent results would be found in this regard. Access to a database detailing investors' wealth levels would also be difficult to obtain. Due to these reasons only income was included as a variable.

Sudman (1980: 430) stated that the most obvious control to use for a shopping mall survey is that of gender. It was, thus, decided that gender as well as education would be used as the two control variables and it was also believed that there would be enough respondents in the other categories for analysis purposes. A target of 30 male and female respondents in each education category was sought, according to the guideline provided by Leedy (1989: 158). In some cases this target was not met and therefore, certain categories were collapsed into others for analysis purposes as is explained in the findings and analysis provided in chapter five. Overall, 327 responses were collected in the survey process and of these, seven were unusable responses. Therefore, the total sample consisted of 320 individual participants. The respondents were surveyed using a questionnaire as the instrument and a discussion of the choice of instrument follows.

4.3 Survey Technique

Risk tolerance, or risk aversion, can either be measured objectively or subjectively as discussed in chapter two. The key determinant of objective and subjective financial risk tolerance is the framework used to measure risk tolerance. The assessment of actual investment behaviour to determine risk tolerance levels is the method favoured by Economists, who try to avoid the direct questioning of individuals, whilst Psychologists who have researched this topic have analysed individual attitudes as the determinant of risk tolerance (MacCrimmon and Wehrung, 1985: 2). However, Subedar *et al* (2006: 6) mentioned certain shortcomings to the objective approach. Firstly, they noted that problems existed with regards to the relationship between age and asset allocation as older investors often have a large portion of their wealth invested in risky, equity asset classes. The issue was that these are generally not a true reflection of their risk tolerance as the investments are as a result of pension and superannuation investment schemes (Subedar *et al*, 2006: 6). Secondly, Subedar *et al* (2006: 6) stated that investors who have the financial means to invest and tolerate losses are biased towards equity type investments. This shows that there are potential biases in using objective measures to assess individual risk tolerance levels. As already mentioned Subedar *et al* (2006: 6) believe that the questionnaire approach, an experimental data collection technique, combines certain aspects of the two methods noted above and is the most widely used method.

Chaulk *et al* (2003: 258) and Hanna *et al* (2001: 54) described that when measuring risk tolerance one can use Economic theory, employing the concept of risk aversion, which was discussed in more detail in the section detailing the Arrow-Pratt measure. Using the Economic framework one measures risk aversion by determining the ratio of risky assets to wealth and it is thus, an objective measure (Chaulk *et al*, 2003: 258 and Chang *et al*, 2004: 54). Perceptions and judgements are also said to influence financial risk tolerance and it is for this reason that it has also been thought of as a subjective construct (Chaulk *et al*, 2003: 259). The various methods that are either objective or subjective in nature are further discussed below.

Hanna and Lindamood (2005: 2) mentioned that, whilst it was important for financial advisors to account for a person's level of risk tolerance, there was no standard or accepted method to measure this. Hanna and Lindamood (2004: 27) previously discussed this, as well as the fact that there was no agreement on how to use the various measures to assist in the portfolio allocation decision. Given the lack of accord on an appropriate measure it was necessary to look to the literature as a guide for selecting the best method. Most studies have used a questionnaire or survey technique involving asking respondents hypothetical questions. Hanna and Lindamood (2004: 29) reasoned that this approach is superior to the others as it provides the strongest link to the concept of risk aversion. Hallahan *et al* (2004: 59) mentioned that the use of questionnaires is the primary risk tolerance assessment method. Subedar *et al* (2006: 6-7) stated that questionnaires draw on facets of both the interview method as well as that of assessing behaviour and is the preferred method as it has the "…ability to gauge an investor's response to a variety of situations that characterise investment decision making under uncertainty." Subedar *et al* (2006: 7) further stated another advantage, being that of the ability to gather demographic information which can be used to categorise investors heuristically and as risk tolerance predictors. It is also argued by Grable and Lytton (1999a: 166) that response biases can be limited, as the use of questionnaires allow for a large number of participants.

The previous literature on measuring risk tolerance has used several methods in an attempt to most effectively quantify risk levels. Hallahan *et al* (2004: 59) and Subedar *et al* (2006: 5) described three basic approaches being that of interviews, assessing actual investment behaviour and assessing responses to hypothetical scenarios and investment choices. As already stated in chapter two, Hanna *et al* (2001: 53) extended this by stating that there were a minimum of four methods for assessing risk tolerance which include "asking about investment choices, asking a combination of investment and subjective questions, assessing actual behaviour, and asking hypothetical questions with carefully specified scenarios." It is evident that the various methods mentioned above are similar in intention but show some differences in assessing risk tolerance.

MacCrimmon and Wehrung (1985: 1) were of the view that there are two components that make up risk taking, being that of the riskiness of a situation and a person's willingness to accept risk. They stated that much research has been conducted on the former with very little on the latter, at that time, and thus, the purpose of their paper was to address this problem. It is highlighted that the measurement of risk tolerance was adapted or different according to the particular discipline of study. In utility theory, choices between gambles are used to define an individual's utility function from which a measure of risk propensity was derived (MacCrimmon and Wehrung, 1985: 1). One of the most common methods of deriving this measure is to use the Arrow-Pratt framework previously discussed in this paper, but MacCrimmon and Wehrung (1985: 1) argue that this measure will not give the same answer across different wealth levels.

Furthermore, it is argued by the authors that the problem is compounded by considering how utility functions are derived. The risk theory requires that an individual choose between two options, a sure payoff or a gamble with two potential outcomes (MacCrimmon and Wehrung, 1985: 1). The individual is then tasked with indicating either a monetary equivalence or a probability equivalence that made them indifferent between the two options and a utility function is obtained either way. The problem arises in that both methods are theoretically correct, however, they do not always result in the same individual utility function and therefore, the measures of risk propensity differ (MacCrimmon and Wehrung, 1985: 2). While MacCrimmon and Wehrung (1985: 2) claimed that the expected utility framework is probably the most highly developed theory, it still has its discrepancies. The evidence suggests that there are indeed various ways used to measure an individual's appetite for risk, however, a researcher needs to determine which is the most appropriate and practical method for their research purposes.

As has been discussed in section 2.4, Anbar and Eker (2010: 505) support the use of a subjective risk tolerance measure, based on the reasoning that an investor's risk tolerance level does not remain constant over time, especially as demographic and economic factors are altered. This makes it necessary for investment managers and financial advisors to account for such factors and continuously update their clients' risk profiles. Chaulk *et al* (2003: 259) also argued that an objective measure would result in some respondents being excluded from their analysis. Their reasoning for this was that younger people and families in their formation years were less likely to have accumulated significant levels of wealth or hold risky assets. Contrastingly, most respondents would have formed attitudes towards financial risk regardless of their financial situation (Chaulk *et al*, 2003: 259). Hanna *et al* (2001: 55) infer that Economic models may not be entirely accurate as well, due to the fact that a large number of households have very low levels of liquid assets and in turn this means they cannot hold high levels of risky assets. As has previously been discussed, Yang (2004: 21) raised the concern that, in using the ratio of risky assets to wealth to measure objective risk tolerance, definitions of risky assets are not always consistent and can result in different assessments. A final concern raised by Yang (2004: 22) was the difficulty and time consuming nature of trying to source detailed individual financial profiles in order to measure the required ratio of risky assets to wealth. This was one of the main reasons behind the decision not to use this approach in this study.

Faff *et al* (2008: 1) used two types of subjective measures, a psychometrically validated survey and a lottery choice experiment, to determine respondents' risk tolerance and risk aversion levels respectively. Furthermore, they proposed to assess whether there was a link between risk tolerance and risk aversion. Their findings suggested that the two measures were strongly aligned and that financial risk tolerance scores were an important predictor of behaviour in the lottery choice experiment (Faff *et al*, 2008: 21). Problems with using the lottery method were, however noted, as it does allow for possible selection bias of which Faff *et al* (2008: 9) mention their study contained certain levels of bias. They stated that experiments of this nature are generally limited to using student samples which could allow for selection bias to arise in two ways (Faff *et al*, 2008: 8). Firstly, they said that "...people might self-select into being a student" and secondly, a bias may arise "...in the type of students who are most likely to respond to advertisements that ask people to participate in experiments" (Faff *et al*, 2008: 8-9). The authors also had to ensure highly detailed instructions were given as it was difficult to control information flow (Faff *et al*, 2008: 9). Another important issue raised which queries the use of lottery experiments is the size of the stakes, as if they are too small real behaviour may not be observed when compared to the actions taken when the stakes are higher (Faff *et al* , 2008: 10). These are all issues that need to be considered when using a lottery approach, which does have its merits. The finding by Faff *et al* (2008: 21) that the two measures were strongly correlated and that the questionnaire approach was a good predictor of lottery behaviour suggest one could employ the questionnaire technique to good effect in future studies.

If one was to use a subjective measure to assess financial risk tolerance it is then important that the most appropriate form of subjective measurement is selected. Lyons, Neelakantan and Scherpf (2008: 69) stated that using interviews was not suitable as it often introduces interviewer bias problems into the study, in that, responses are not always accurate. Subedar *et al* (2006: 6) are of the opinion that the major weakness of using interviews or informal discussions with investors about their previous and current portfolio compositions to determine objective risk tolerance levels is that they are not scientific or objective "...and do not provide any substance for investment advisors to provide advice on." However, Grable and Lytton (1999a: 165) acknowledged that objective measures are commonly used but the deduction of a person's risk tolerance from their asset holdings could pose serious validity concerns. The reason for this is that objective measures are based on the assumptions that investors behave rationally and that an individual's asset allocation is a personal choice as opposed to advice from a financial advisor. It is further stated that objective measures tend to be descriptive rather than predictive, do not account for the different dimensions of risk and generally cannot explain actual investor behaviour (Grable and Lytton, 1999a: 165). Lyons *et al* (2008: 60) also queried the use of objective Economic measures due to the lack of consensus about the relationship between wealth and risk aversion. They mention that there is still debate as to whether the ratio of risky assets to wealth increases, decreases or remains constant when wealth increases (Lyons *et al*, 2008: 60).

MacCrimmon and Wehrung (1990: 423) provided an interesting discussion on what the best method of measuring an individual's willingness to take on levels of financial risk is. They stated that "...no measure of risk propensity is free of problems and so it seems desirable to obtain data on a variety of measures. Clearly one wants to include measures with theoretical backing, but these should be supplemented with measures based on real choices and ones that are understandable and meaningful to practicing risk takers" (MacCrimmon and Wehrung, 1990: 423). Another problem which adds to this dilemma in choice is that an individual who shows a certain risk propensity in one situation may not necessarily show the exact same risk propensity in another situation (MacCrimmon and Wehrung, 1985: 3). For example, a person who shows a risk loving appetite when facing favourable opportunities may exhibit entirely different characteristics when feeling threatened or, alternatively, a person who enjoys taking on business related risks might not enjoy risk from a personal perspective. Due to this, MacCrimmon and Wehrung (1985: 3) added that it would be preferable if one could analyse these different scenarios so as to identify "...if there are any systematic differences in risk propensity across different situations."

More recently, Corter and Chen (2006: 371) have referred to the combination of the measures discussed above as measuring risk tolerance as a 'cross-situational disposition' as opposed to being 'situation-specific'. In their study Corter and Chen (2006: 372) used a risk tolerance questionnaire, after concluding, from an analysis of the previous literature, that there was strong support for risk being a domain specific concept rather than one that should factor in other domains such as MacCrimmon and Wehrung (1985: 3) suggest. One such study was that conducted by Weber *et al* (2002: 263) whose study concentrates on assessing risk perceptions and behaviours by using a domain-specific risk-attitude scale. The domains (financial, health/safety, recreational, ethics and social) studied by Weber *et al* (2002: 268) were defined after an extensive review of previous risk-related literature sources. Their results, as also discussed by Corter and Chen (2006: 372), provided support for the notion that risk attitudes were domain-specific (Weber *et al*, 2002: 282). Thus, it was concluded that in order to measure individual financial or investment risk attitudes a specific investment risk tolerance measure was the most appropriate technique to use and hence, the choice of a risk tolerance questionnaire in their study (Corter and Chen, 2006: 372).

The confusion in the choice of a risk tolerance measurement tool is not limited to these studies, as one will see below, however, there is enough evidence to suggest the questionnaire method is widely accepted and supported. The use of the other methods discussed above in conjunction with that of the questionnaire approach provides an ideal opportunity for further research into this topic.

4.4 Survey Instrument

As discussed previously, the study by Strydom *et al* (2009) used a variant of the Hanna and Lindamood (2004: 37) questionnaire. This particular method involved the modelling of hypothetical pension/income based scenarios and required the respondents to make decisions based on a 50 percent chance that, as the sole income earner in a family, their income would be doubled or a 50 percent chance that there would be a certain percentage loss (Hanna and Lindamood, 2004: 29). The income cut (percentage loss) ranged from five percent to 50 percent. Included in the Strydom *et al* (2009) study was a separate question on investment risk tolerance taken from the SCF, where the respondents were required to choose one of the four following statements which best describes their investment strategies:

1. Substantial financial risks expecting to earn substantial returns
2. Above-average financial risks expecting to earn above-average returns
3. Average financial risks expecting to earn average returns
4. No financial risks

This question was also discussed by Kimball *et al* (2007: 5) as a way of ordering respondents into different risk tolerance categories. The SCF question has been used extensively in studies [see Hawley and Fujii (1994), Embrey and Fox (1997), Hanna *et al* (2001), Coleman (2003), Chang *et al* (2004), Yao *et al* (2005) and Gilliam *et al* (2008)] and therefore, it was included in this study to allow for a comparison between the results drawn from the main instrument used in the study (which is discussed further below).

As discussed previously the Hanna and Lindamood (2004) questionnaire has its limitations, in that a certain level of financial knowledge is needed to answer all the questions and it did not account for the different dimensions of financial risk tolerance, thus, an alternative instrument was sought for the purposes of this study. It is believed that the questionnaire discussed below accounts for these issues as it measures financial risk tolerance with respect to eight different dimensions of financial risk and not all the questions are difficult to answer. Grable and Lytton (1999a: 172) do observe that some may consider certain items of the questionnaire used as quite complex and difficult to understand for those who are not considered to be well educated, and may argue that this could have adversely affected an individual's response and hence, the results. However, Grable and Lytton (1999a: 172) specifically include these questions as they deduced, from their review of previous literature, that risk tolerance is related to experience and knowledge of financial issues and they suggested that a person who "...answers aggressively to these items should, on average, be more risk tolerant than others."

Along with being user-friendly the Grable and Lytton (1999a) questionnaire was rigorously tested for both validity and reliability, as is discussed below, and therefore, the testing of these issues do not necessarily need to be conducted when using this questionnaire. Peterson (2000: 79) explains reliability as the "...consistency or dependability in measuring whatever it [a questionnaire] is designed to measure."

Whilst validity is the "...extent to which a [questionnaire] measures what it is designed to measure" (Peterson, 2000: 79). These definitions are supported by Leedy and Ormrod (2005: 28-29).

Grable and Lytton (1999a: 163) provided an interesting view on measuring risk tolerance in their study, which was purely devoted to the development of a risk assessment instrument. The authors followed the rule that when creating an instrument, firstly, items must be selected, then analysed, after which index scores are created and finally, one must test for index and instrument validity and reliability (Grable and Lytton, 1999a: 168). Originally a potential 100 assessment items or questions were identified, however, after proceeding through the necessary steps mentioned before, this was narrowed down to just 20 items. These 20 items were said to measure a variety of dimensions of financial risk (Grable and Lytton, 1999a: 174). According to Grable and Lytton (1999a: 174) the dimensions said to be measured by the 20 items are listed as follows:

1. guaranteed versus probable gambles;
2. general risk choice;
3. choice between sure loss and sure gain;
4. risk as related to experience and knowledge;
5. risk as a level of comfort;
6. speculative risk;
7. prospect theory; and,
8. investment risk.

Supporting the use of the categories listed above, the authors acknowledged that alone none of the items would be able to provide a true evaluation of financial risk tolerance, however, when used as a combined measure the accuracy would be greatly enhanced (Grable and Lytton, 1999a: 174). Furthermore, to ensure an even more improved measure, the authors performed principal component factor analysis on each of the 20 items. This phase served two purposes which in the authors' own words were to "[ensure] that within the 20 items the instrument offered a multidimensional approach to financial situations yet focused on the central concept of risk. The second purpose of the factor analysis was the elimination of items that did not significantly contribute to the measurement of the underlying dimensions. This ensured that the instrument was brief, nonredundant, and interesting to complete" (Grable and Lytton, 1999a: 176). The factor analysis approach was said to include four statistical criteria which are the eigenvalue-one criterion, the screen test, the proportion of variance accounted for and the interpretability of the resulting factors.

As a result of the above mentioned analysis, seven items of the questionnaire were deemed to be unsuitable and the remaining 13 items were further tested for validity. Following the validity test, by comparing the assessment tool to the SCF risk tolerance question, it was concluded that, in comparison, the 13 item risk assessment tool measured a wider variety of financial risk components. Overall, the authors proved that the final 13 items met the requirements "for a multidimensional financial risk-tolerance assessment instrument" (Grable and Lytton, 1999a: 178).

Grable and Lytton (2003: 257) completed a follow-up study on this risk tolerance assessment tool in order to conduct a more rigorous test of its validity. It is noted that in the previous study the authors were able to test the construct validity of the instrument but were unable to test for criterion-related validity (Grable and Lytton, 2003: 258). The construct validity of an instrument refers to how meaningful an item or index is in multiple situations, whilst the criterion-related validity is defined as how accurate an item or index is in explaining actual behaviour (Grable and Lytton, 2003: 258). As such the purpose of their research was to extend the Grable and Lytton (1999a) study by examining the criterion-related validity of the 13-item financial risk tolerance assessment instrument. Two key components in measuring the criterion-related validity were that of accuracy and consistency and according to Grable and Lytton (2003: 258), "...if the scale produces an accurate measurement of the construct, the results would, therefore, be consistent."

Grable and Lytton (2003: 258-9) determined, in their research, that in order to measure the accuracy of such a tool the content-related, criterion-related and construct-related validity of the tool needs to be evaluated. Content-related validity applies to the extent to which the content, or topics, of the measure were representative of the theory surrounding the construct and is present when the questions are viewed as being relevant by subject matter experts (Peterson, 2000: 79 and Roszkowski, Davey and

Grable, 2005: 74). Logical or sampling validity are other terms that could be used to refer to content validity (Grable and Lytton, 2003: 259). According to Grable and Lytton (2003: 259), "[c]riterion-related validity reflects the relationship between the data-gathering tool and one or more criteria, or measurements, known or believed to be representative of the attribute or behaviour under study." Roszkowski *et al* (2005: 74) explained that this type of validity represents the relationship between the risk tolerance test score and a separate measure of behaviour related to the test construct (the criterion). There are typically two types of criterion-related validity, referred to as concurrent and predictive validity (Peterson, 2000: 79-80 and Roszkowski *et al*, 2005: 74). Thirdly, construct-related validity measures the extent to which the tool reflects the personality or psychological construct it is meant to measure (Grable and Lytton, 2003: 259) or why a tool measures what it is designed to measure (Peterson, 2000: 80).

The authors highlighted that the assessment of the validity of the risk tolerance measurement tool is extremely complex but it is vital in ensuring the quality of the tool (Grable and Lytton, 2003: 259). Furthermore, Grable and Lytton (2003: 260) stated that the result of a validity test is bolstered if the criterion and predictor variables are founded in a theoretical framework. It was further stated by Grable and Lytton (2003: 260) that, "Modern Portfolio Theory provides an ideal theoretical framework when identifying and evaluating criterion, both predicted and predictive, related to financial risk tolerance attitudes and behaviors." Based on this it is hypothesized that actual financial risk-taking behaviours should be correlated with financial risk tolerance. Accordingly, the authors stated that if the Grable and Lytton (1999a) 13-item risk tolerance assessment tool was valid, the resulting scores from the tool should correspond to actual investment behaviours (Grable and Lytton, 2003: 261).

An initial validity test of the 13-item instrument was conducted by comparing it against the SCF financial risk tolerance question and it was found that there was a positive relationship between the two and therefore, provided some support for the criterion validity of the Grable and Lytton (1999a) assessment tool (Grable and Lytton, 2003: 262). The method used to assess the validity of the instrument was divided into two parts. The first step was to calculate validity coefficients between risk tolerance scores and investment portfolio asset allocations. According to Grable and Lytton (2003: 262), this test was for concurrent criterion validity as the data for both measurements were gathered simultaneously. The second step involved multivariate analyses (using OLS regression) "...used to consider the same relationships in the context of selected demographic factors which have been thought to be influential" (Grable and Lytton, 2003: 262). An internet based survey was used for data collection and the final sample of usable responses consisted of 303 respondents. These respondents were said to have satisfied the prerequisites of having investable assets and making their own investment decisions and this ensured that the criterion was relevant, reliable and bias free (Grable and Lytton, 2003: 263). The authors stated the main research hypothesis as follows, "...risk tolerant investors should, holding other factors constant, own a higher proportion of high-risk, high expected return assets (such as stocks) rather than low-risk, low expected return assets (such as bonds or cash)" (Grable and Lytton, 2003: 264).

The results showed moderate support for the concurrent validity of the 13-item risk tolerance instrument with a validity coefficient of 0.31 ($p < 0.001$). The positive correlation was consistent with the original proposition that an increased score on the instrument (greater risk tolerance) translated into increased ownership of equities (Grable and Lytton, 2003: 266). On the other hand the validity coefficient of -0.32 ($p < 0.001$) indicating the correlation between the scale score and the proportion of fixed income securities and cash owned by the respondent implied an inverse relationship as was expected by Grable and Lytton (2003: 266).

In their discussion, Grable and Lytton (2003: 268) concluded that the results derived were consistent with MPT. It was also stated that the positive relationship between risk tolerance and ownership of equities (as a proportion of savings and investment assets) and the negative relationship between financial risk tolerance and ownership of fixed income securities and cash, supported the criterion-related and construct-related validity of the 13-item financial risk tolerance assessment tool (Grable and Lytton, 2003: 268). Given these results it was also acknowledged that the tool is not the definitive or perfect risk tolerance instrument, but if used with another client assessment tool, a more improved and informed decision as to an individual's risk tolerance level can be made (Grable and Lytton, 2003: 268). Grable and Lytton (2003: 269) explained that the ideal situation would be to have a model that explains more than 70 percent of a person's risk attitude, however, this is not the case. It is further stated that, "[t]he fact that an instrument designed to assess risk-taking attitudes explains less than 25% of actual risk-taking behaviour is not surprising, given the complexity of the construct" (Grable and Lytton, 2003: 269).

Another important finding subsequent to the factor analysis was that the 13-item questionnaire was said to measure financial risk tolerance based on three constructs, namely, investment risk, risk comfort and experience, and speculative risk. These three constructs encapsulated the 8 different dimensions of financial risk discussed above (Grable and Lytton, 1999a: 177). According to Grable and Lytton (1999a: 177) questions four (D), five (E), eight (H), eleven (K) and twelve (L) (see the questionnaire in Appendix B) assessed the willingness of a respondent to take direct investment risks. These questions combined "…the attributes of knowledge and temperament in the assessment of risk tolerance" (Grable and Lytton, 1999a: 174). These attributes determine how respondents deal successfully with emotional investments (Grable and Lytton, 1999a: 174). Questions one (A), three (C), six (F), seven (G) and thirteen (M) (see the questionnaire in Appendix B) were said to measure the construct of risk comfort and experience (Grable and Lytton, 1999a: 177). Grable and Lytton (1999a: 172) commented that these items required an understanding of interest rates, mortgage markets and investing – some of the original questions that measured this construct were removed in the final questionnaire (see Grable and Lytton, 1999a). The level of comfort in taking risky decisions applies to the fact that certain people share psychological traits that encourage risk taking (Grable and Lytton, 1999a: 172). It was stated that in terms of comfort and experience individuals with a higher risk tolerance would feel a sense of confidence and satisfaction from making a risky decision whilst less risk tolerant individuals would be averse to making such decisions (Grable and Lytton, 1999a: 173).

With regards to speculative risk items two (B), nine (I) and ten (J) (see the questionnaire in Appendix B) provided a way of measuring this construct (Grable and Lytton, 1999a: 177). These items ensured that respondents were forced to either select a safe option or speculate on the degree of return offered in a certain situation (Grable and Lytton, 1999a: 173). Questions nine, described in terms of gains, and ten, described in terms of losses, were adapted from Prospect Theory, according to Grable and Lytton (1999a: 173-174). Respondents who selected the sure choice were said to be characterised as risk averse, whilst those who chose the gamble option were more likely to be risk loving

(Grable and Lytton, 1999a: 174). A respondent who chose the sure choice in one question and the gamble in the other suggests a moderate level of risk tolerance (Grable and Lytton, 1999a: 174). Based on this, Grable and Lytton (1999a: 177) stated, therefore, that the instrument allowed for a high degree of multidimensionality in assessing risk tolerance levels. More importantly, the combination of all 13 questions together helped in the assessment of the probability of gains, the probability of losses, the dollar amount of potential gains, the potential dollar loss through the assessment of guaranteed versus probable gambles, minimum probability of success given a risky course of action and minimum returns given a risky course of action (Grable and Lytton, 1999a: 177-178).

In order to place individuals into a risk tolerance category, weights (or scores) were assigned to each possible answer for each question and subsequently totalled to determine which risk category best characterises the respondent. The weights had a maximum range of one to four with the higher the weighting the more risky the choice and *vice versa* (Grable and Lytton, 1999a: 168). A risk tolerance score was then derived by summating the scores that corresponded to a participant's choice of response (Grable and Lytton, 1999a: 168-169; 175). In the Grable and Lytton (1999a: 175) study the authors, according to their results, categorised respondents as being highly risk tolerant, moderately risk tolerant or having a low level of risk tolerance (highly risk averse). How they categorised the respondents was not explained and although not implicitly stated, the highest score one could obtain using the 13-item instrument was 47, where the respondent would obviously have chosen the option with the highest associated risk level for every question. At the opposite end of the scale the lowest score was 13 whilst the mean would have been 30. Using these scores one could determine the risk tolerance categorisations, however, it was more appropriate to base them on the actual responses gathered, such as was done in the Grable and Lytton (1999b: 3-4) study. In the study, the authors using the questionnaire that consisted of 20 items, categorised respondents as either having an above average level of risk tolerance or a below average risk tolerance (Grable and Lytton, 1999b: 3-4). The scores ranged between 19 and 63 and the mean was 37, therefore, those that scored under 37 were considered to be below average risk tolerant and those equal to or higher than 37 to be above average risk tolerant (Grable and Lytton, 1999b: 4).

It can be seen that the Grable and Lytton (1999a) 13-item instrument has been tested quite extensively and been subjected to rigorous analyses techniques. It has been shown that the 13-items cover the categories and dimensions of risk required in the assessment of the overarching concept of financial risk tolerance (Grable and Lytton, 1999a: 177) and therefore, a similar South African adapted version was used for this study and allowed for a more robust analysis of the concept of financial risk tolerance (please see Appendix B for a copy of this questionnaire). The only adaptations that were made to the original questionnaire was to change some of the financial terms from the US accepted term to one that South Africans would be more familiar with. The reason for this was to allow for the respondents in the study to gain a better understanding of the questions asked using wording and terms that they were familiar with. The SCF question, as discussed previously, was also included in the questionnaire that was completed by the respondents.

Although it has been mentioned that the Grable and Lytton (1999a) instrument has been quite extensively tested the internal reliability of the adapted scale for this study (the questionnaire measuring financial risk tolerance) was also tested using Cronbach's alpha, which is said to calculate the "...average of all possible split-half reliability coefficients" (Bryman and Cramer, 2009: 77). Al-Ajmi (2008: 19) commented that the reliability of an item or scale is how free it is from measurement error. The Cronbach alpha coefficient calculated was 0.742 which indicates that the scale had a high level of internal reliability. According to Pallant (2007: 98) values above 0.70 are acceptable. In testing their own instrument Grable and Lytton (1999a: 177) found that the Cronbach alpha was 0.7507 which was at the upper end of the range (0.5 to 0.8) that ensured consistency. The study by Anbar and Eker (2010: 509) also used the Grable and Lytton (1999a) instrument and conducted this step, however, their result was lower at 0.61. The reliability of the Grable and Lytton (1999a) instrument was also tested in the study by Yang (2004: 22), using Cronbach's alpha, and it was said to have had a high level of reliability of 0.7507, which was the same as that of Grable and Lytton (1999a: 177).

The following section details the choice of statistical model that adequately suited the data requirements and the statistical tests conducted.

4.5 Method of Analysis

The previous study by Strydom *et al* (2009), although good in many aspects, had a major weakness in the methodology, as the isolated use of nonparametric techniques limited the analysis of the data. Whilst the Strydom *et al* (2009: 19) study was able to draw some important conclusions in line with international research, the median analysis method employed in the paper could be argued as one if its shortfalls. The reason for this, noted by the authors, was that this type of analysis did not enable them to properly test the relationship between the demographic factors (independent or explanatory variables) and risk tolerance (dependent variable). The most obvious example of this was the relationship between risk aversion and race and risk aversion and religion and this was acknowledged by Strydom *et al* (2009: 18) as they stated that "[i]t is, however, not easy to interpret the true significance of these results as obviously a major overlap exists between the racial and religious classifications."

Although, median analysis was conducted as part of this study, one of the main aims was to overcome the problem highlighted in the Strydom *et al* (2009) study, by employing a more robust analysis technique, allowing for such comparisons, known as a Binary Logistic model and an explanation of this model follows. "Binary Logistic" is the term used by the statistical programme SPSS, which was used in this study and hence the term is used in this explanation. It is acknowledged that certain authors refer to this model using other terms as is explained later in this section. The statistical analysis procedures performed in this study were very similar to those used by Anbar and Eker (2010: 509) who also used the Grable and Lytton (1999a) survey that has already been discussed. The many similarities in the studies provide support for the chosen methodological techniques applied. A motivation for the use of Binary Logistic model is given by Anbar and Eker (2010: 510), who claimed that this type of model was preferred to other similar techniques (e.g. regression analysis and discriminant analysis) as there are less stringent assumptions. It was said that a logistic regression does not assume a linear relationship between the dependent and independent variables, does not require the variables to be normally distributed and homoscedasticity was not assumed (Anbar and Eker, 2010: 511). The treatment of the demographic factors as explanatory variables is also covered later in this section.

4.5.1 Dependent Variable

It is important to define the dependent variable used in this study as this was another factor that supported the use of the Binary Logistic procedure. As already covered in the previous section, the use of the Grable and Lytton (1999a) survey allows for an individual risk tolerance score to be calculated for every respondent that completed the questionnaire. Following this, it was then possible to determine the minimum and maximum score obtained as well as the mean which was used as a way of classifying respondents as either below or above average risk tolerant. Table 4-1 below presents this data.

Table 4-1: Risk Tolerance Score Sample Statistics

N	Valid	320
	Missing	0
Mean		26.18
Std. Deviation		5.804
Range		31
Minimum		14
Maximum		45

As the table above shows, there were 320 risk tolerance scores obtained, the minimum score was 14 and the maximum was 45. The resultant mean score for the sample was 26.18 (standard deviation = 5.804). In similar fashion to Grable and Lytton (1999b: 4) and Anbar and Eker (2010: 508), respondents who scored below 26.18 were categorised as being below average risk tolerant and those that scored above 26.18 were categorised as being above average risk tolerant. In total there were 166 respondents who were below average risk tolerant (51.9% of the sample) and 154 who were above average risk tolerant (48.1%). These results were very similar to those of Anbar and Eker (2010: 508) and are shown in Table 4-2. Below average risk tolerant respondents were then coded “1” and above average as “2” as SPSS automatically codes them as “0” and “1”, respectively, when estimating the Binary Logistic model. The dependent variable can thus, be defined as a categorical variable. A categorical variable indicates the presence, or absence, of an attribute or quality and is more commonly referred to as a dummy variable, for which the value is either 0 or 1 (Gujarati, 1988: 432).

Table 4-2: Risk Tolerance Categorisation Sample Statistics

	Frequency	Percent
Below Average Risk Tolerant	166	51.9
Above Average Risk Tolerant	154	48.1
Total	320	100.0

It is, therefore, quite obvious now that risk tolerance, as the dependent variable in this study, consisted of two categories and an appropriate statistical model was needed. Before an explanation of the Binary Logistic model used in this study is provided it is necessary to examine the various independent variables included so that one has a better understanding of the overall model used.

4.5.2 Independent Variables

Table 4-3, shown over the page, presents a summary of the independent variables and their various categories. It is important to note all the variables, except age, were categorical.

Gujarati (1988: 431) stated that the inclusion of qualitative variables "makes the linear regression model an extremely flexible tool that is capable of handling many interesting problems encountered in empirical studies". As already mentioned a categorical variable is treated as a dummy variable where, for example, the value 0 may represent a male respondent and 1, a female respondent. According to Gujarati (1988: 432), qualitative, or dummy, variables can be included in a regression model just as one would use quantitative variables.

Table 4-3: Independent Variables

Variables	Categories
Age	None
Gender	Male
	Female
Education	Less than Matric
	Matric
	Less than 3 Year Post Matric Study
	3 Year Undergraduate Degree/Diploma
	Postgraduate Degree
Marital Status	Single
	Married
	Divorced
Race	Black
	Coloured
	Indian
	White
Annual Household Income (Income)[3]	Less than R150 000
	Greater than R150 001 but less than R235 000
	Greater than R235 001 but less than R325 000
	Greater than R325 001 but less than R455 000
	Greater than R455 001 but less than R580 000
	Greater than R580 001
Religion	Christian
	Hindu
	Muslim
	Jewish
	Other

It is important to note that when introducing dummy variables the chance of encountering perfect multicollinearity is high and thus the rule to be followed is, if a qualitative variable has m categories there must be m – 1 dummy variables in the model (Gujarati, 1988: 436). Not abiding by this rule could lead to the model falling into the "dummy variable trap" (i.e. multicollinearity) which, according to Gujarati (1988: 284), results in potentially more than one linear relationship between the explanatory

[3] The income categories used were taken from the South African Revenue Services (SARS) guidelines for individual income tax (SARS, 2011).

variables. For ease of computation, SPSS deals with the coding of the dummy variables automatically.

4.5.3 The Binary Logistic Model

As already noted, for all the independent variables investigated, except age, the responses were categorical (e.g. male or female for gender) and thus, qualitative in nature (Gujarati, 1988: 431). Furthermore, by classifying respondents into different risk ‘classes’, as a result of their calculated risk scores shown in section 4.5.1, the dependent or response variable was defined as a categorical variable as well. Koop (2008: 278) explains that the standard regression models used in econometric modelling are inappropriate when the dependent variable is a dummy variable. His reasoning for this is that the classical assumption of a normally distributed dependent variable is violated in this case and therefore, models that can deal with variables such as these need to be used (Koop, 2008: 278).

Models with qualitative dependent variables fall into the group of econometric models known as discrete choice models, or otherwise referred to as qualitative response models, quantal or categorical models (Amemiya, 1986: 267; Hill, Griffiths and Judge, 1997: 198; Davidson and MacKinnon, 2004: 466 and Koop, 2008: 277). Within this group of models there exist the binary choice models or univariate dichotomous models (Verbeek, 2000: 178 and Koop, 2008: 278). These models are used to model the decision between two discrete alternatives where a linear regression is inappropriate. Many authors, including Amemiya (1986: 268); Gujarati (1988: 468); Hill *et al* (1997: 198); Verbeek (2000: 178); Brooks (2007: 646) and Koop (2008: 278), explain these models in their works. The most basic of these models is the linear probability model, however, this model has its limitations and therefore, two alternative models, the probit model and the logit model are more commonly used (Gujarati, 1988: 480). The probit and logit models are very similar except that their assumptions around the error terms differ. A probit model assumes the errors follow the standard normal distribution while the logit model assumes they are logistically distributed (Kennedy, 2003: 260 and Koop, 2008: 279). According to Koop (2008: 343) a normally distributed variable has a mean μ and variance σ^2 and is denoted $X \sim N(\mu, \sigma^2)$ and follows the common bell-shaped distribution. Following from this if the error terms are assumed to follow the standard normal distribution then $\mu = 0$ and $\sigma^2 = 1$. The logistic distribution differs from the normal distribution in that $\sigma^2 = \pi^2/3$ whilst $\mu = 0$ and the standard logistic distribution function has slightly heavier tails than the standard normal distribution (Amemiya, 1986: 269). In comparing the use of the two models (probit and logit) Amemiya (1986: 269) commented that a justification for using logit models is that the logistic distribution function is similar to the normal distribution function "...but has a much simpler form."

As the model formulations are very similar a researcher needs to decide on the most appropriate model based on mathematical convenience and also consider the availability of computer programs that have either of these models as a function (Gujarati, 1988: 496). To this end, Gujarati (1988: 496) stated that the logit model is more commonly used based on these factors. Furthermore, Gujarati and Porter (2010: 388) commented that the two models generally provide similar results but that the logit model is more popular due to its comparative mathematical simplicity. Hill, Griffiths and Lim (2008: 425) also supported this notion as they claimed that the probit model is "...numerically complicated because it is based on the normal distribution." Whilst Kennedy (2003: 260) comments that the logit model is more common.

It is evident that there is theoretical support for the use of a Binary Logistic (or logit) model which is further supported by the fact that there have also been other studies which have used this type of model in similar fashion. The study by Sung and Hanna (1996: 13) conducted a logit analysis as their dependent variable took on two values: no risk and risk tolerant. Their independent variables were also very similar, in that they were categorical demographic factors (Sung and Hanna, 1996: 14), to those used in this study. Hanna and Lindamood (2005: 6) also created a dichotomous dependent variable in their study which consisted of the categories "some risk" and "no risk". In their analysis they used a "...logistic regression (logit), which is an appropriate multivariate analysis to use with dichotomous dependent variables..." (Hanna and Lindamood, 2005: 7). As already discussed, the study conducted by Anbar and Eker (2010: 509) also used a logistic regression "...to determine the influence of the sociodemographic variables on financial risk tolerance."

As is evident by their name these dichotomous models are often used, but not limited to, when constructing models that have, as their dependent variable, a choice between two alternatives, for example, the decision by an individual to drive to work or catch a bus (Koop, 2008: 279). The model can just as easily be applied to a situation where respondents are categorised into one of two groups, as it is still a dummy variable, and thus, it is applicable for the purposes of this study (Pallant, 2007: 166 and Kennedy, 2003: 259).

A Binary Logistic model is typically captured by the following formula (Verbeek, 2000: 180, Dwyer *et al*, 2002: 154 and Koop, 2008: 279):

$$Y_i^* = \beta X_i + \varepsilon_i, \tag{4-1}$$

Where the dependent variable, Y_i^*, is unobserved, X_i is a vector of person-specific exogenous variables (explanatory variables), β is the estimated response coefficient vector and ε_i is the random error term (Dwyer *et al*, 2002: 154).

Y_i^* is unobservable (Koop, 2008: 279) but one is able to observe the risk tolerance category in which an individual falls. Therefore, if a respondent in the study is below average risk tolerant, $Y_i = 0$ is observed and $Y_i = 1$ is observed for an above average risk tolerant respondent. Pallant (2007: 166) commented that, a logistic regression allows one to, "...test models to predict categorical outcomes with two or more categories" where the independent variables can be categorical or continuous, or a combination of both. Following this, the particular model estimated in this study is shown below:

$$RTCAT_i = \alpha + \beta_i Age_i + \beta_i Gender_i + \beta_i Education_i + \beta_i MaritalStatus_i + \beta_i Race_i + \beta_i Income_i + \beta_i Religion_i + \varepsilon_i, \tag{4-2}$$

Where: $RTCAT_i$ = 1 if the respondent is above average risk tolerant, 0 otherwise (below average risk tolerant);

Age_i = the age of the respondent;

$Gender_i$ = the gender of the respondent;

$Education_i$ = the education category of the respondent;

$MaritalStatus_i$ = the marital status of the respondent;

$Race_i$ = the race of the respondent;

$Income_i$ = the household income category of the respondent; and,

$Religion_i$ = the religion category of the respondent.

All of the variables in formula 4-2 have already been defined and explained in sections 4.5.1 and 4.5.2. It must be noted that when estimating a Binary Logistic model with categorical or dummy independent variables one of the categories is treated as the base or reference category and comparisons are made with this category (Gujarati, 1988: 437). According to Gujarati (1988: 437), the decision as to which category within a variable is treated as the reference category is a matter of choice. SPSS allows one to use either the first or last category as the reference category in estimating the model. For consistency reasons the first category for each variable was used as the reference category, however, when necessary the last category has been used as will become evident in the findings and analysis of the study.

Subsequent to the estimation of formula 4-2 using the Binary Logistic procedure in SPSS one can then conduct various statistical tests to determine the appropriateness of the model and whether there were any significant relationships between the explanatory variables and the dependent variable. As such the main hypotheses tested, as part of the study, are detailed below.

4.5.4 Study Hypotheses

<u>Hypothesis 1: The effect of age on risk tolerance</u>

It is evident from the literature reviewed in the previous chapter that there is support for the life-cycle hypothesis, that risk tolerance decreases with age. This was found to be the case in the studies by Morin and Suarez (1983: 1210) and Schooley and Worden (1996: 92) amongst others. However, it was also noted that some studies found that the relationship was in fact negative and thus, disputed the life-cycle hypothesis, whilst some studies found that there was no relationship between risk tolerance and age. As such the null hypothesis that age has no effect on risk tolerance was tested, and is shown in mathematical format as follows:

$H_0: \beta_1 = 0$

$H_1: \beta_1 \neq 0$

The testing of this hypothesis allowed an analysis of the life-cycle theory to be conducted with the available South African data.

Hypothesis 2: The effect of gender on risk tolerance

The review of the literature which analysed the relationship between gender and risk tolerance found, overwhelmingly, that males were considered to be more risk tolerant or risk loving than females. However, some interesting points of discussion arose from the various studies regarding this relationship and the findings. The first point was the concern surrounding the concept of statistical discrimination between females and males which was discussed in the literature review. Linked to this issue, previous studies have stressed that it is important for financial advisors to be considerate in terms of properly measuring and assessing an individual's risk tolerance rather than assuming or discriminating according to gender. In order to determine whether females are more risk averse than their male counterparts, the second relationship hypothesized was:

$H_0: \beta_2 = 0$

$H_1: \beta_2 \neq 0$

Where the acceptance of the null hypothesis suggests that there was no difference in risk tolerance between males and females.

Hypothesis 3: The effect of education on risk tolerance

Consensus amongst the majority of studies was that education was positively related to an individual's appetite for risk and that this could be related to the fact that an improved education generally leads to a higher income earning potential. Therefore, there may have also been an income effect. Four such studies were those by Hartog *et al* (2000: 11), Sung and Hanna (1996: 14), Donkers *et al* (2001: 185) and Schooley and Worden (1996: 93). As such the following hypothesis was tested, where the null hypothesis states that education level has no effect on risk tolerance.

H_0: $\beta_3 = 0$

H_1: $\beta_3 \neq 0$

Hypothesis 4: The effect of marital status on risk tolerance

The previous literature regarding the effect marital status has on risk tolerance levels found that there was indeed a causal relationship between the two variables and that generally, it was found that single individuals were the most risk tolerant. Two such studies that investigated this were those of Riley and Chow (1992: 34) and Yao *et al* (2005: 56). Based on this, the null hypothesis that marital status has no effect on risk tolerance was tested and is shown below:

H_0: $\beta_4 = 0$

H_1: $\beta_4 \neq 0$

Hypothesis 5: The effect of race on risk tolerance

The evidence from the studies which analysed the relationship between race and risk tolerance provided very mixed or conflicting results. Some of the international studies to investigate this relationship were those by Riley and Chow (1992: 34) who found that the differences across racial categories in terms of risk tolerance were small; Bellante and Green (2004: 277) who found that Whites were more risk tolerant than other races and Sahm (2007: 39) who found that Whites were more risk tolerant than Blacks and Hispanics. The South African study by Gumede (2009: 24 and 34) found that White respondents had a greater willingness to take on higher levels of financial risk. The other South African study by Strydom *et al* (2009: 17) found that there was a significant difference in risk tolerance between Whites and Blacks as well as Whites and Indians. The results from these papers provide justification for the testing of the null hypothesis that there was no difference in risk tolerance across racial/ethnic categories seen below:

H_0: $\beta_5 = 0$

H_1: $\beta_5 \neq 0$

Hypothesis 6: The effect of household income on risk tolerance

The notion that there is a positive relationship between income and risk tolerance found overwhelming support from the studies which examined this, including those of Hartog *et al* (2000: 10-14), Grable and Lytton (1999b: 6), Al-Ajmi (2008: 21-22) and Christiansen *et al* (2009: 8-9). Interestingly, in the study by Morin and Suarez (1983: 1210) income was found to be the most important determinant of risk aversion levels and thus, provided good reason for the investigation of the null hypothesis that there was no difference in risk tolerance across income brackets:

H_0: $\beta_6 = 0$
H_1: $\beta_6 \neq 0$

Hypothesis 7: The effect of religion on risk tolerance

As already mentioned in the study, there was limited evidence on the relationship between religion and risk tolerance, however, two studies which did find a relationship were that of Barsky *et al* (1997: 549) and Halek and Eisenhauer (2001: 22). Therefore, the seventh null hypothesis stated that there was no difference in risk tolerance across religious groups and is given below:

H_0: $\beta_7 = 0$
H_1: $\beta_7 \neq 0$

The statistical tests used to test these hypotheses and other aspects of the Binary Logistic model are discussed next.

4.5.5 Statistical Analysis

The main analysis technique employed in this study was that of the Binary Logistic model, which has already been discussed, however, non-parametric tests were also conducted in order to draw direct comparisons with the Strydom *et al* (2009) and Anbar and Eker (2010) studies who used this method. The Strydom *et al* (2009) study only used non-parametric tests in their study and this has already been argued as one of its weaknesses and hence, the reasoning behind improving the analysis by using the Binary Logistic procedure. A description of the non-parametric tests used is provided below, following that the various tests used when conducting the Logistic analysis are discussed.

4.5.5.1 Non-parametric Tests

Similar to Strydom *et al* (2009: 10) and Anbar and Eker (2010:509) non-parametric tests in the form of the Mann-Whitney U Test and the Kruskal-Wallis test together with median analyses were conducted on the data for additional investigative purposes. According to Roscoe (1969: 7) and Pallant (2007: 210), non-parametric tests are suitable when data being measured is either nominal or ordinal. It is also important to note that there are limitations associated with the use of non-parametric tests as according to Norušis (2006: 384) they generally do not find true differences and the hypotheses tested are sometimes different as one tests hypotheses about the medians (it must be noted that in this study the Binary Logistic results were used for hypothesis testing). Nevertheless, the tests were still conducted in order to compare the results to similar studies. A Mann-Whitney U Test was used for the variable “Gender” as it is the appropriate test to use when there are two groups to the variable (Norušis, 2006: 394 and Roscoe, 1969: 175), whilst all the other variables were tested using the Kruskal-Wallis technique as it is applicable to variables with three or more groups (Norušis, 2006: 396 and Agresti, 1984: 182). The Mann-Whitney U and Kruskal-Wallis test are computed in very similar ways where the combined data values of the two groups, for Mann-Whitney U, are ranked and then the average rank is determined (Norušis, 2006: 394). The only difference for the Kruskal-Wallis test is that there are more than two groups (Norušis, 2006: 396). Instead of using the risk tolerance categories as the dependent variable for these tests one is required to use a continuous variable (Pallant, 2007: 220) and therefore, the actual scores were used. Furthermore, the variable “Age” was categorised to allow for ease of testing.

4.5.5.2 Correlation Tests for the Binary Logistic Model

One of the first steps conducted, when using a Binary Logistic model, is to check for the existence of multicollinearity caused by a high level of intercorrelation between the independent variables (Pallant, 2007: 167). The reasoning for this is that this type of model is sensitive to high correlations between the explanatory variables (Pallant, 2007: 169). According to Pallant (2007: 126) and Baddeley and Barrowclough (2009: 20), the strength and direction of the linear relationship between two variables can be described by using correlation analysis. SPSS offers the options of calculating three different correlation coefficients (Pearson product-moment coefficient, Spearman rho and Kendall's tau) (Pallant, 2007: 126 and Norušis, 2006: 486-7). According to Norušis (2006: 486) the latter two measures are appropriate for variables measured at an ordinal level and therefore, are suited to this study. The Spearman's rho was used in this study as it is appropriate for measuring non-parametric correlations.

4.5.5.3 Goodness of Fit Tests for the Binary Logistic Model

In order to test the model for goodness of fit, SPSS automatically produces an Omnibus Tests of Model Coefficients which provides an overall indication of the performance of the model (Pallant, 2007: 174), as well as the Hosmer and Lemeshow Test which also is an indication of support for the model (Bewick, Cheek and Ball, 2005: 115). For the Omnibus Tests of Model Coefficients one wants a highly significant value which is less than 0.05 and as such indicates a good fit. Judging a model by the Hosmer and Lemeshow Test one seeks a value that is greater than 0.05, representing a good fit (Pallant, 2007: 174). Ideally, a model would satisfy both of these tests, however, in the event that there are contrasting results the Hosmer and Lemeshow Test is regarded as the most reliable (Pallant, 2007: 174).

4.5.5.4 Hypothesis Tests in the Binary Logistic Model

The results produced from the Binary Logistic procedure in SPSS allow one to test the effect of the explanatory variables on risk tolerance and therefore, test the study hypotheses, by using what is referred to as the Wald test (Pallant, 2007: 175). The Wald test is an alternative to the more commonly used F-test but it is a favoured method when the model estimated is non-linear or the errors are distributed non-normally [the F-test is used for joint hypothesis testing under the assumption of the classical normal linear regression model] (Kennedy, 2003: 66). The Wald test is said to be distributed asymptotically as a Chi-square (χ^2) with degrees of freedom that are equal to the number of restrictions that are being tested (Kennedy, 2003: 67).

When using a Binary Logistic model there are other tests which can be used, such as the likelihood-ratio test, but according to Hauck and Donner (1977: 851) there is an advantage of using the Wald test "[d]ue to the iterative nature of maximum likelihood estimation when applied to logit analysis…" Hauck and Donner (1977: 851) commented that the Wald test can be used to test hypotheses as is shown below. If one wants to test the hypothesis that:

$$H_0: \beta_k = \beta_{k0} \text{ vs } H_1: \beta_k \neq \beta_{k0} \tag{4-3}$$

Then let β^*_k be the maximum likelihood estimate of β_k and H is the inverse of the sample information matrix (Hauck and Donner, 1977: 851). According to Hauck and Donner (1977: 851) the Wald test statistic for equation 4-3 is:

$$W = (\beta^*_k - \beta_{k0})^2/H_{kk} \tag{4-4}$$

Where: H_{kk} is the estimated variance of β^*_k (Hauck and Donner, 1977: 851).

Verbeek (2000: 162) confirms that the test statistic follows a Chi-squared distribution and states that large values for W lead to the rejection of the null hypothesis.

Some sources such as Bewick *et al* (2005: 114) interpret equation 4-4 into the following, more simplistic, formula for the Wald test statistic:

$$W = (\text{coefficient/SE coefficient})^2 \tag{4-5}$$

Where: SE coefficient is the standard error of the coefficient.

Fortunately, for ease of use, the Wald statistic and its significance value are computed in the model's output by SPSS and instead of testing hypotheses based on the magnitude of the Wald statistic, one can use the computed significance value (Pallant, 2007: 175). According to Pallant (2007: 175), significance values that are below 0.05 are viewed as being highly significant. B values (representing the beta coefficients), either positive or negative, are used as an indication of the direction of the relationship between a certain independent variable and risk tolerance. The odds ratio provides further support for this as a ratio that is less than one corresponds to a negative B value and a ratio more than one should be evident for a positive B value (Pallant, 2007: 176). Anbar and Eker (2010: 511) stated that the odds ratio is "...the probability of the outcome event occurring divided by the probability of the event not occurring and the odds ratio for a predictor tells the relative amount by which the odds of the outcome increase (odds ratio greater then 1.0) or decrease (odds ratio less than 1.0) when the value of the predictor value is increased by 1.0 units."

From the discussion above it can be seen that there are a variety of ways to measure risk tolerance and the appropriate technique is often reliant on the availability of data. As such, a subjective questionnaire was chosen for the purposes of this study as data on asset holdings is particularly hard to access and conducting a survey requesting individuals for this data was deemed not feasible. It is acknowledged though that this approach has been used in other studies, however, these studies measured objective risk tolerance. As outlined, the sampling procedure was carried out using the mall intercept method and a sample of respondents was collected at the various shopping malls which allowed for the data analysis to be conducted. The statistical procedures used in the study included non-parametric techniques as well as the Binary Logistic model. Using the results from the Binary Logistic model the Wald test was then used to determine the significance of the demographic variables and conduct hypothesis tests. The results from the various statistical techniques are presented in chapter five, as part of the findings and analysis of the study which follows next.

5 FINDINGS AND ANALYSIS

The following chapter presents the findings and analysis from the study. The first part details the descriptive statistics of the study sample, whilst the second examines the non-parametric tests carried out after which the various Binary Logistic regression models used to analyse the data are discussed. These models were used to determine if there was a significant relationship between a certain demographic variable and risk tolerance. Hypothesis testing was conducted based on these results.

5.1 Sample Descriptive Statistics

Table 5-1 shows the overall sample statistics in terms of how many observations were recorded for each of the explanatory variables.

Table 5-1: Sample Statistics

		Gender	Education	Age	Race	Income	Marital Status	Religion
N	Valid	320	320	319	320	316	320	318
	Missing	0	0	1	0	4	0	2

As was stated previously in the methodology chapter, a total of 320 usable responses were gathered from the survey, however, in some cases respondents did not complete all the demographic data required in the questionnaire. This is not a serious issue as SPSS allows one to treat those "non-responses" as missing values and allows for the exclusion of the corresponding respondent in the analysis when necessary. The table shows that for age there was one missing response, whilst for income and religion there were, respectively, four and two omissions.

The following tables show the descriptive statistics with respect to the variables age, gender, education, race, income, marital status and religion.

Table 5-2: Age

N	Valid	319
	Missing	1
Mean		41.03
Range		68
Minimum		17
Maximum		85

Age was the only non-categorical variable used in the analysis, where there were 319 recorded observations (one missing observation). The mean age was 41.03 years, whilst the youngest respondent was 17 years and the oldest was 85 years. The remaining explanatory variables were all categorical and their respective frequencies are detailed below.

Table 5-3: Gender

		Frequency	Percent
Valid	Male	172	53.8
	Female	148	46.3
	Total	320	100.0

It is obvious from the table that of the total of 320 respondents 172 were male (53.8%) and the remaining 148 (46.3%) were female.

Table 5-4: Education

		Frequency	Percent
Valid	Matric or less	121	37.8
	3 Year Undergraduate Degree/Diploma or less (but higher than Matric)	133	41.6
	Postgraduate Degree	66	20.6
	Total	320	100.0

For the variable “Education”, there were five original categories (explained in section 4.5.2), collapsed into the three shown above for analysis purposes, due to the small number of respondents in some categories. The first category, an education level of Matric or less, had 121 observations (37.8%). For the category 3 Year Undergraduate

Degree/Diploma or less there were 133 observations (41.6%) and there were 66 respondents (20.6%) who fell into the Postgraduate Degree category.

Table 5-5: Race

		Frequency	Percent
Valid	Black	65	20.3
	Coloured	37	11.6
	Indian	81	25.3
	White	137	42.8
	Total	320	100.0

In total there were 65 Black (20.3%) respondents, 37 Coloured (11.6%) respondents, 81 Indian (25.3%) respondents and 137 white (42.8%) respondents in the sample.

Table 5-6: Household Income

		Frequency	Percent
Valid	<R150 000	132	41.3
	R150 001<R235 000	84	26.3
	R235 001<R325 000	48	15.0
	R325 001<R455 000	25	7.8
	R455 001<R580 000	11	3.4
	>R580 001	16	5.0
	Total	316	98.8
Missing		4	1.3
Total		320	100.0

For the variable “Income”, 132 (41.3%) of the respondents fell into the category of less than R150 000 (including zero) and 84 respondents (26.3%) were in the second category (greater than R150 001 but less than R235 000). There were 48 observations (15.0%) for the category of greater than R235 001 but less than R325 000, 25 observations (7.8%) for the greater than R325 001 but less than R455 000 category, 11 observations (3.4%) in the category of greater than R455 001 but less than R580 000 and finally, 16 respondents (5.0%) indicated their household incomes were greater than R580 001. There were also the four missing responses recorded.

Table 5-7: Marital Status

		Frequency	Percent
Valid	Single	135	42.2
	Married	164	51.3
	Divorced	21	6.6
	Total	320	100.0

In terms of Marital Status there were 135 single respondents (42.2%), 164 married respondents (51.3%) and 21 divorcees (6.6%) in the sample.

Table 5-8: Religion

		Frequency	Percent
Valid	Christian	259	80.9
	Hindu	37	11.6
	Muslim	16	5.0
	Jewish	1	.3
	Other	5	1.6
	Total	318	99.4
Missing		2	.6
Total		320	100.0

The majority of respondents, 259 (80.9%), indicated, for religion, that they fell into the Christian category. Hindus totaled 37 (11.6%) of the sample, there were 16 Muslim (5.0%) respondents, one Jewish respondent (0.3%) and five (1.6%) in the category “Other”. As already mentioned there were also two omissions.

As discussed in the methodology the next step in the analysis of the data was to conduct non-parametric tests and in so doing draw a direct comparison to the study by Strydom *et al* (2009) as well as the results obtained by Anbar and Eker (2010) using similar tests. The testing of the actual study hypotheses is based on the results from the Binary Logistic model which are discussed in section 5.3.

5.2 Non-parametric Test Results

5.2.1 Mann-Whitney Test and Median Analysis for Gender

A Mann-Whitney test concluded that there was a significant difference (p = 0.012) in the risk tolerance scores of males (median = 27, n = 172) and females (median = 25, n = 148). The median scores suggest males were more risk tolerant than females. This finding is consistent with the studies by Anbar and Eker (2010: 513) and Strydom *et al* (2009: 15).

Table 5-9: Mann-Whitney U Test for Gender

	Risk Tolerance Score
Mann-Whitney U	10658.000
Wilcoxon W	21684.000
Z	-2.512
Asymp. Sig. (2-tailed)	.012

Table 5-10: Median Analysis for Gender

Gender	N	Median
Male	172	27.00
Female	148	25.00
Total	320	26.00

5.2.2 Kruskal-Wallis Tests and Median Analyses for Remaining Explanatory Variables

Table 5-11 shows that there was a statistically significant difference in risk tolerance across the age categories used (p = 0.030) with the median values suggesting that risk tolerance decreases with age. Anbar and Eker (2010: 514) found that age had no significant effect on risk tolerance, whilst Strydom *et al* (2009) did not investigate this. The Kruskal-Wallis test for education was significant at the five percent level (p = 0.043) and the median values suggested that those respondents (n = 66) who had a postgraduate degree were more risk tolerant than the other categories. This finding is consistent with the study by Anbar and Eker (2010: 515). Strydom *et al* (2009) did not include education in their study. The Kruskal-Wallis χ^2 statistic of 18.933 for income indicated that there was a significant difference ($p = 0.002$) in risk tolerance among the income categories with the median analysis suggesting the respondents in the higher income categories were more risk tolerant than those in the lower categories. Those in the second highest category (greater than R455 001 but less than R580 000) had the highest median score of 33.00. This result was similar to the finding of Anbar and Eker (2010: 515), whilst Strydom *et al* (2009: 18) found no significant difference.

The results from the Kruskal-Wallis test for marital status concluded that there was a significant difference ($p = 0.006$) in risk tolerance scores across the different categories. Single respondents (n = 135) had the highest median of 27, the married respondents' median was 26, whilst the median for divorcees was 22. Anbar and Eker (2010: 514) found that there were no significant differences in risk tolerance according to marital status and Strydom *et al* (2009) did not investigate this variable. The Kruskal-Wallis test for race revealed that there was no significant difference ($p = 0.370$) in risk tolerance scores between the different categories although Black respondents (n = 65) did record the highest median of 27. This was in contrast to the finding by Strydom *et al* (2009: 16), whereas, Anbar and Eker (2010) did not examine the effects of race. Similar to the results for race, there was no significant difference in risk tolerance among the religion categories ($p = 0.329$) but Muslims (n = 16) had the highest median (27.50). Strydom *et al* (2009: 18) did find significant differences but questioned whether their results were due to the overlap with race. The effects of religion on risk tolerance were not studied by Anbar and Eker (2010).

As has already been discussed, non-parametric tests are characterised by certain limitations most notably that one cannot control for the effects of other variables when conducting them and therefore, a more improved technique, the Binary Logistic method, was used to test the hypotheses in this study. These results are detailed after the presentation of Table 5-11 (over the page).

Table 5-11: Median Analyses and Kruskal-Wallis Test Results

Variables	Financial Risk Tolerance				
Age	n	Median	χ^2	df	Sig. (p)
17<25	77	27.00	10.677	4	.030
26<35	71	27.00			
36<45	52	25.00			
46<65	88	24.50			
65<100	31	23.00			
Education					
Matric or less	121	26.00	6.302	2	.043
3 Year Undergraduate Degree/Diploma or less	133	26.00			
Postgraduate Degree	66	27.50			
Income					
<R150 000	132	26.00	18.933	5	.002
R150 001<R235 000	84	24.50			
R235 001<R325 000	48	26.00			
R325 001<R455 000	25	28.00			
R455 001<R580 000	11	33.00			
>R580 001	16	27.00			
Marital Status					
Single	135	27.00	10.139	2	.006
Married	164	26.00			
Divorced	21	22.00			
Race					
Black	65	27.00	3.142	3	.370
Coloured	37	26.00			
Indian	81	25.00			
White	137	26.00			
Religion[4]					
Christian	259	26.00	2.225	2	.329
Hindu	37	23.00			
Muslim	16	27.50			

[4] There was only one Jewish respondent and only five respondents in the "Other" category therefore, these were omitted in the analysis.

5.3 Binary Logistic Model Results

As per the statistical analyses outlined in section 4.5.5 of the methodology the results are presented below.

5.3.1 Spearman's Rho Correlation Coefficients

The following table shows the Spearman's Rho correlation coefficients among the explanatory variables in the study:

Table 5-12: Spearman's Rho Correlation Coefficients

Scale	1	2	3	4	5	6	7
1. Age	-	.111*	-.103	.548**	.316**	.100	-.054
2. Gender		-	-.026	.136*	.232**	-.021	-.059
3.Education			-	-.087	.114*	.311**	-.033
4. Marital Status				-	.172**	.273**	.052
5. Race					-	.101	-.093
6. Income						-	.058
7. Religion							-

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

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

As can be seen from the table above there is no evidence that the variables are extremely highly correlated with one another. The highest correlation occurs between Age and Marital Status (r = 0.548). It is acknowledged that this is considered a large strength correlation according to the guidelines provided by Pallant (2007: 132), but it is only just above the 0.50 guideline and therefore, is not of major concern.

5.3.2 Goodness of Fit Statistics

The first Binary Logistic model estimated produced results that satisfied the goodness of fit statistics providing support for the model. More specifically, the model returned a Chi-square value of 34.251 with 18 degrees of freedom and was significant at the five percent level (p = 0.012), χ^2 (18, N = 313, $p < 0.05$). The Hosmer and Lemeshow Test statistic of 8.490 had a significance level of 0.387 which is larger than the required value of 0.05 therefore, providing further support for the model. The results from this regression are shown in Table 5-13 below and were used for the hypothesis testing procedures which follow.

Table 5-13: Binary Logistic Model 1[5]

	B	S.E.	Wald	df	*p*	Odds Ratio
Age	-.018	.009	4.190	1	.041	.982
Female	-.588	.254	5.336	1	.021	.555
Education(1)			2.295	2	.317	
Education(2)	-.323	.288	1.256	1	.262	.724
Education(3)	.123	.357	.118	1	.731	1.130
Single			4.129	2	.127	
Married	.160	.314	.260	1	.610	1.174
Divorced	-.997	.606	2.709	1	.100	.369
Black			2.740	3	.433	
Coloured	-.106	.475	.050	1	.823	.899
Indian	-.570	.520	1.200	1	.273	.566
White	.214	.356	.362	1	.547	1.239
Income(1)			9.523	5	.090	
Income(2)	-.255	.314	.661	1	.416	.775
Income(3)	-.015	.377	.002	1	.968	.985
Income(4)	.766	.490	2.448	1	.118	2.151
Income(5)	1.575	.832	3.582	1	.058	4.831
Income(6)	.779	.597	1.702	1	.192	2.178
Christian			1.822	4	.769	
Hindu	.219	.567	.149	1	.699	1.245
Muslim	.804	.692	1.351	1	.245	2.235
Jewish	-20.826	40192.970	.000	1	1.000	.000
Other	-.631	.947	.444	1	.505	.532
Constant	.972	.427	5.165	1	.023	2.642

[5] The education categories included Matric or less, 3 Year Undergraduate Degree/Diploma or less (but higher than Matric) and Postgraduate Degree respectively. For income the respective categories were <R150 000, R150 001<R235 000, R235 001<R325 000, R325 001<R455 000, R455 001<R580 000 and >R580 001. These orderings apply to all other models with these variables included, unless otherwise stated.

5.3.3 Hypothesis Testing

5.3.3.1 Age and Risk Tolerance

The hypothesis that age has no effect on risk tolerance was tested, using the Wald statistic outlined in section 4.5.5.4 and this is shown as follows:

H_0: $\beta_1 = 0$
H_1: $\beta_1 \neq 0$

The Wald statistic of 4.190 was statistically significant at the five percent level (p = 0.041). Based on this, one can reject the null hypothesis that age has no effect on risk tolerance and therefore, conclude that there is a significant relationship. This follows Verbeek's (2000: 162) rule that large values for W lead to the rejection of the null hypothesis. As such $\beta_1 \neq 0$ and it follows from the model that $\beta_1 = -0.018$. The negative value for β_1 suggests that as age increases risk tolerance moves in the opposite direction, or decreases. This was also confirmed by the odds ratio in the model being below one (0.982).

These results are consistent with the expectation that risk tolerance is likely to decrease with age and are in line with the international studies by Morin and Suarez (1983: 1210), Schooley and Worden (1996: 92), Hallahan *et al* (2004: 75) and Jianakoplos and Bernasek (2006: 999). Whilst Anbar and Eker (2010: 514) concluded in their study, that age had no significant effect on risk tolerance based on their ANOVA tests. The finding that risk tolerance decreases as an individual ages lends support to the idea that younger investors have a greater investment horizon and more chance of recovering potential losses and therefore, enjoy taking on higher levels of risk. As Al-Ajmi (2008: 8) explained, younger individuals can, if they desire, replace leisure time with more work and decrease current consumption in order to recover any investment portfolio losses. Neither of the two South African studies reviewed investigated the relationship between age and risk tolerance and therefore, these results provide new evidence from a South African perspective.

5.3.3.2 Gender and Risk Tolerance

The relationship between gender and risk tolerance was tested using the following hypothesis:

H_0: $\beta_2 = 0$
H_1: $\beta_2 \neq 0$

The model produced a Wald statistic of 5.336 for the female category of respondents and was significant at the five percent level ($p = 0.021$). The high Wald statistic and the fact that it was significant at the five percent level infer that gender and risk tolerance are related, with $\beta_2 = -0.588$, and therefore, the null hypothesis that $\beta_2 = 0$ can be rejected. Similar to the finding with age, the negative value for β_2 indicates that female respondents are less likely to fall in the above average risk tolerance category. The odds ratio of 0.555, which is below one, supports this finding. Therefore, this result provides further support for the notion that females are less risk tolerant than males. It must be highlighted though that this is a general result for females and therefore, all females may not be below average risk tolerant.

The finding that men are more risk tolerant than women in this study is similar to studies such as those by Pålsson (1996: 785), Hartog *et al* (2000: 11), Hallahan *et al* (2004: 67), Hanna and Lindamood (2004: 34) and Al-Ajmi (2008: 21-22). The results from the logistic regression in the study by Anbar and Eker (2010: 512-513) also suggested that women were more risk averse than men. The study by Gumede (2009: 22 and 33) found that there was no significant difference in risk tolerance between males and females, whilst, consistent with this study, Strydom *et al* (2009: 15)[6] found that more men preferred higher levels of risk, whereas, women favoured lower levels. A possible reason for this finding may be that historically, in South Africa women have often played a secondary role in society compared to men, however, this is changing as female empowerment is being encouraged and over time these results may be different in a future study. Strydom *et al* (2009: 3) mentioned that the differences may be due to

[6] It is acknowledged that Strydom *et al* (2009) only used non-parametric test procedures however, the results from the logistic regression are still compared. A comparison of non-parametric results has already been carried out in section 5.2.

objective constraints where females' lower risk tolerance levels are linked to lower levels of personal investment in human capital. Alternatively, Strydom *et al* (2009: 3) commented that there also exists a school of thought that believes the difference is brought on by subjective constraints in that women are less confident and more conservative than men and this is confirmed by Powell and Ansic (1997: 607). Furthermore, the study by Chen and Volpe (2002: 290) stated that gender differences in risk tolerance can also be affected by an individual's understanding of financial knowledge. The level of financial knowledge itself was not measured in this study, however, one can argue that education could be used as a proxy for the understanding of financial knowledge and therefore, it was decided to test whether there was any difference in risk tolerance between less educated males (those with a Matric or less) and more educated females (those with more than a Matric). This was done using a Mann-Whitney test and the results are presented as follows:

Table 5-14: Mann-Whitney U Test for Gender and Education

	Risk Tolerance Score
Mann-Whitney U	2536.000
Wilcoxon W	6452.000
Z	-.734
Asymp. Sig. (2-tailed)	.463

Table 5-15: Median Analysis for Gender and Education

Gender	Median	N
Male	27.00	62
Female	26.00	88
Total	26.00	150

Unfortunately, the Mann-Whitney U test was not significant as it had a *p*-value of 0.463, however, the median analysis does show that even when considering less educated males they still have a greater risk tolerance than the more educated females in this sample.

Although, these results support the general perception that women have less appetite for risk compared to men it is still not safe to assume that this is the case for all females.

Financial advisors are again cautioned against discriminating against females and assuming they are automatically less risk tolerant than their male counterparts because of their gender. Individual risk analysis should always be conducted in order to appropriately determine an investor's risk appetite and therefore, match the required investment portfolio to the correct risk tolerance level. Based on this the null hypothesis that there is no difference in risk tolerance between males and females can be rejected.

5.3.3.3 Education and Risk Tolerance

The following hypothesis was tested in order to determine whether there was any significant relationship between education and financial risk tolerance:

H_0: $\beta_3 = 0$
H_1: $\beta_3 \neq 0$

The model produced a Wald statistic of 2.295, 1.256 and 0.118 for each of the respective education categories [Matric or less, 3 Year Undergraduate Degree/Diploma or less (but higher than Matric) and Postgraduate Degree] which are quite low, particularly for the last category. Furthermore, none of the categories were statistically significant with the respective *p*-values being 0.317, 0.262 and 0.731. These results suggest that education does not have a significant effect on risk tolerance levels and therefore, one cannot reject the null hypothesis that β_3 = 0. These results make it necessary to investigate whether education has an effect on risk tolerance when analysed in isolation with the use of a univariate Binary Logistic model, the results of which are shown below.

Table 5-16: Univariate Binary Logistic Model with Education

	B	S.E.	Wald	df	*p*	Odds Ratio
Education(1)			4.734	2	.094	
Education(2)	-.141	.252	.313	1	.576	.868
Education(3)	.521	.312	2.794	1	.095	1.684
Constant	-.116	.182	.405	1	.525	.891

The results show that when analysed separately the first category and third category are significant ($p < 0.10$) using the Wald test. This would suggest that a respondent, in this study, who has a postgraduate degree qualification is more risk tolerant than a respondent with a Matric or less (the reference category) as the β value is positive (0.521) and the odds ratio is greater than one (1.684). In terms of goodness of fit, although the data from the Omnibus Tests of the Model Coefficients was insignificant at the required five percent level, χ^2 (2, N = 319, $p > 0.05$ [$p = 0.09$]), the Hosmer and Lemeshow Goodness of Fit statistic of 1.000 is substantially greater than the required 0.05. Pallant (2007: 174), comments that the Hosmer and Lemeshow Goodness of Fit test is the most reliable test available in SPSS and therefore, one can accept these results.

It is acknowledged that the difference in results from the full multivariate model and the univariate model suggest that there is some evidence of multicollinearity. This is due to the fact that when education was analysed separately two of the categories were significant at the ten percent level whereas all the categories were largely insignificant in the full model. If one refers back to Table 5-12 which presents the correlation coefficients it is evident that the correlation between income and education (0.311) is significant at the one percent level. This is despite the coefficient falling under the rule of thumb guideline of 0.5 and suggests that there may be evidence of multicollinearity between the two variables.

The findings as to how risk tolerance was affected by education level are inconclusive and suggest that there is no significant difference in risk tolerance across the education categories. These results are in contrast to the many studies, such as Donkers *et al* (2001: 185), Bellante and Green (2004: 277), Chang *et al* (2004: 64) and Kimball *et al* (2007: 20), that found that there was a significant relationship and that risk tolerance generally increased with education level. The study by Anbar and Eker (2010: 516) also found that education, with respect to the department a student studied in, had a significant effect on risk tolerance. The South African study by Gumede (2009: 27) also did not find a significant result in terms of education, whilst the Strydom *et al* (2009) study did not investigate this relationship. The inconclusive results may be attributed to the fact that the educational categories could have been better defined (e.g. a distinction made between respondents with a degree or diploma) as well as increasing the sample size and ensuring that all the categories meet the minimum number of respondents required so that no categories would be collapsed. This would help in ensuring a more diverse sample of respondents with respect to their educational background.

5.3.3.4 Marital Status and Risk Tolerance

The fourth hypothesis tested in the study was whether marital status had any effect on risk tolerance. The hypothesis was tested as follows:

H_0: $\beta_4 = 0$

H_1: $\beta_4 \neq 0$

The reference category of being single, although having a high Wald statistic of 4.129, was statistically insignificant with p = 0.127. The results for the other two categories suggested that being married had no effect on risk tolerance, however, being divorced was found to have a marginally significant effect at the ten percent level. The Wald statistic for being married was 0.260 and the p-value was 0.610, whilst they were 2.709 and 0.100 respectively for being divorced. According to this one then fails to reject the null hypothesis that marital status has no effect on risk tolerance and therefore, that β_4 = 0. A larger sample may prove otherwise given that both the single and divorced categories had p-values that were close to being significant at the ten percent level. Given these results further analysis was then conducted by using a univariate regression in order to determine if there were any differences in the findings and the results are presented in Table 5-17 below.

Table 5-17: Univariate Binary Logistic Model with Marital Status

	B	S.E.	Wald	df	p	Odds Ratio
Single			5.241	2	.073	
Married	-.135	.233	.338	1	.561	.873
Divorced	-1.237	.541	5.239	1	.022	.290
Constant	.074	.172	.185	1	.667	1.077

The Goodness of Fit statistics prove that this model performs well and was statistically significant, χ^2 (2, N = 319, $p < 0.05$ [$p = 0.049$]) and the Hosmer and Lemeshow statistic of 1.000 was greater than the required 0.05. In this model the category for divorcees was found to be significant at the five percent level ($p = 0.022$) with a Wald statistic of 5.239 and had an odds ratio of 0.290 and a negative β value confirming that divorced respondents are less risk tolerant than single respondents. The category for single respondents was also significant but at the ten percent level (Wald statistic = 5.241 and $p = 0.073$). These findings suggest that in the full multivariate model these effects are possibly being subsumed by another variable with age being a potential candidate. The reason for this is that a lot of the single respondents were younger than those that were divorced and therefore, more risk tolerant based on their age. The following table shows that none of the respondents in the category 17 to 25 were divorced, with the most divorcees (nine) falling in the age category 46 to 65. In contrast over fifty percent (73) of the single respondents fall into the youngest age category (17 to 25).

Table 5-18: The Relationship between Age and Marital Status

		Marital Status			
		Single	Married	Divorced	Total
Age	17<25	73	4	0	77
	26<35	34	30	6	70
	36<45	9	38	5	52
	46<65	7	72	9	88
	66<100	11	19	1	31
Total		134	163	21	318

Further tests were conducted to determine whether gender and marital status, together, had an effect on risk tolerance. As such, a model with marital status for males was estimated separately from that of females to see if there were any differences. The results are shown in the tables over the page.

Table 5-19: Univariate Binary Logistic Model with Marital Status (for males)

	B	S.E.	Wald	df	*p*	Odds Ratio
Single			.945	2	.623	
Married	-.137	.316	.187	1	.665	.872
Divorced	-.645	.682	.894	1	.344	.525
Constant	.239	.220	1.185	1	.276	1.270

Table 5-20: Univariate Binary Logistic Model with Marital Status (for females)

	B	S.E.	Wald	df	*p*	Odds Ratio
Single			3.891	2	.143	
Married	-.016	.356	.002	1	.964	.984
Divorced	-2.106	1.086	3.761	1	.052	.122
Constant	-.197	.281	.489	1	.485	.821

The results for the male respondents suggest that marital status has no significant effect on their risk tolerance, however, for females there is some evidence supporting the relationship. The category for female divorced respondents is significant at the ten percent level (p = 0.052) and the β value of -2.106 and an odds ratio less than one (0.122) prove that this group of respondents is less risk tolerant than single females (the reference category). Overall, these findings imply that marital status makes more of a difference for the female participants than the males in this survey. Further research is recommended though using a larger sample to analyse these relationships more extensively.

A Kruskal-Wallis test was also conducted to test whether marital status affected males and females differently and the results are shown in Tables 5-21 and 5-22 below.

Table 5-21: Kruskal-Wallis Test for Gender and Marital Status

	Risk Tolerance Score (Females)	Risk Tolerance Score (Males)
Chi-Square	7.705	2.674
df	2	2
Asymp. Sig.	.021	.263

Table 5-22: Median Analysis for Gender and Marital Status

	Females		Males	
Marital Status	N	Median	N	Median
Single	51	26.00	84	27.50
Married	85	26.00	78	27.00
Divorced	11	22.00	10	22.00
Total	147	25.00	172	27.00

The Kruskal-Wallis results suggest that there was a significant difference across the marital status categories for female respondents (p = 0.021) but not for males (p = 0.263). The median analysis for female respondents concluded that single and married respondents were the most risk tolerant compared to divorcees. This finding suggests that marital status plays a more important role in determining risk tolerance levels for females compared to males.

The results are in contrast to Anbar and Eker (2010: 516) who found that marital status had no significant effect on risk tolerance at all, as well as Chaulk *et al* (2003: 274). However, the studies by Barber and Odean (2001: 285) and Hallahan *et al* (2004: 71), found that single individuals were more risk tolerant than those who were married. Both Strydom *et al* (2009) and Gumede (2009) did not investigate this relationship. This result seems plausible when one considers that an individual who was previously married and is now divorced may be less risk tolerant as household income would generally decrease and one may need to save more. Single respondents are often not accountable to a spouse or dependents (it is acknowledged that some single respondents may have partners or dependents and therefore, this is merely suggestive) and can therefore, take on higher levels of risk without concern for the effect on their partner or those dependent on them. Therefore, the relationship between marital status and risk tolerance was further investigated by determining whether having dependents had any effect on risk tolerance overall and then separately for single, married and divorced respondents respectively.

Other studies which investigated similar problems were those by Bellante and Green (2004: 269) and Christiansen *et al* (2009: 1). However, none of the models (the full univariate model or the selective models) produced any significant results (see the tables below for these results). The study by Bellante and Green (2004: 276-277) found that the number of children did not significantly influence risk tolerance levels, however, when they included housing as a risky asset in their model the number of children was significant (Bellante and Green, 2004: 279), this is in contrast to the finding of this study. Similar to the latter result found by Bellante and Green (2004: 279), Christiansen *et al* (2009: 8) also found that having children living at home had a significant negative effect on the willingness of an individual to invest.

Table 5-23: Univariate Binary Logistic Model with Dependents

	B	S.E.	Wald	df	*p*	Odds Ratio
Dependents	.113	.230	.241	1	.623	1.120
Constant	-.113	.143	.620	1	.431	.893

Table 5-24: Univariate Binary Logistic Model for Single Respondents and Dependents

	B	S.E.	Wald	df	*p*	Odds Ratio
Dependents	.000	.431	.000	1	1.000	1.000
Constant	.074	.193	.148	1	.700	1.077

Table 5-25: Univariate Binary Logistic Model for Married Respondents and Dependents

	B	S.E.	Wald	df	*p*	Odds Ratio
Dependents	.380	.316	1.447	1	.229	1.462
Constant	-.265	.231	1.308	1	.253	.767

Table 5-26: Univariate Binary Logistic Model for Divorced Respondents and Dependents

	B	S.E.	Wald	df	*p*	Odds Ratio
Dependents	-.405	1.041	.152	1	.697	.667
Constant	-.981	.677	2.099	1	.147	.375

Further analysis is needed with a bigger sample to test whether marital status, in its entirety has a significant effect not just some of the categories.

5.3.3.5 Race and Risk Tolerance

The relationship between race and risk tolerance was tested according to the following hypothesis:

H_0: $\beta_5 = 0$
H_1: $\beta_5 \neq 0$

The Wald statistics produced by the model were 2.740, 0.050, 1.200 and 0.362 for Blacks, Coloureds, Indians and Whites, respectively, which are generally quite low. The *p*-values were, in the same order, 0.433, 0.823, 0.273 and 0.547 and were all highly insignificant. Based on these results one fails to reject the null hypothesis that $\beta_5 = 0$. However, when the model was rerun with the Whites category as the reference category[7] the results proved that Indians ($p = 0.095$) were significant at the ten percent level (see Table 5-28). The results show that Indians (Wald statistic = 2.795, $p = 0.095$, $\beta = -0.829$ and an odds ratio of 0.437) were in fact less risk tolerant than Whites in this sample. This suggests that the null hypothesis that there is no difference in risk tolerance across racial/ethnic categories can be rejected and therefore, $\beta_5 \neq 0$. The finding that Whites are more risk tolerant than Indians was interesting considering that the study by Strydom *et al* (2009: 17) found the opposite. Strydom *et al* (2009: 17) suggested that Whites were significantly less risk tolerant than both Blacks and Indians in their study. It was thought that possibly income was capturing some of the effects for race in that there was a possibility that Whites had higher incomes than Indians and may therefore, be more risk tolerant. However, a comparison of the number of Indians versus Whites in the various income categories does not lend a great deal of support to this notion. Table 5-27 shows that a higher percentage of Indians (20.51%) actually fall into the top three income categories compared to Whites (16.18%). These findings suggest that further research into the relationship between race and risk tolerance is necessary.

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[7] One will recall from the methodology section that the reference category selected is a matter of choice (Gujarati, 1988: 437).

Table 5-27: Income Levels for Whites and Indians

	Income						Total
	<R150 000	R150 001 <R235 000	R235 001 <R325 000	R325 001 <R455 000	R455 001 <R580 000	>R580 001	
Indian	33	16	13	8	4	4	78
White	52	38	24	12	3	7	136
Total	85	54	37	20	7	11	214

Table 5-28: Binary Logistic Model 2 (with White as the reference race category)

	B	S.E.	Wald	df	*p*	Odds Ratio
Age	-.020	.009	4.863	1	.027	.981
Female	-.574	.257	5.004	1	.025	.563
Education(1)			2.895	2	.235	
Education(2)	-.353	.289	1.498	1	.221	.702
Education(3)	.162	.359	.204	1	.652	1.176
White			3.077	3	.380	
Black	-.248	.358	.480	1	.489	.780
Coloured	-.362	.420	.743	1	.389	.697
Indian	-.829	.496	2.795	1	.095	.437
Income(1)			10.378	5	.065	
Income(2)	-.262	.314	.696	1	.404	.769
Income(3)	-.033	.378	.008	1	.930	.968
Income(4)	.750	.491	2.337	1	.126	2.117
Income(5)	2.315	1.092	4.495	1	.034	10.122
Income(6)	.764	.599	1.631	1	.202	2.148
Single			4.206	2	.122	
Married	.210	.317	.441	1	.507	1.234
Divorced	-.949	.608	2.434	1	.119	.387
Christian			1.705	4	.790	
Hindu	.213	.572	.139	1	.709	1.238
Muslim	.779	.697	1.248	1	.264	2.179
Jewish	-20.833	40192.970	.000	1	1.000	.000
Other	-.625	.947	.435	1	.509	.535
Constant	1.252	.509	6.048	1	.014	3.497

A Mann-Whitney U Test was also conducted to see whether there was a significant difference between Whites and Indians in terms of risk tolerance. The results are shown below, however, one observes that there is no significant difference ($p = 0.564$) between the two categories using the Mann-Whitney U Test. Nevertheless, the comparison of the medians confirms that Whites are more risk tolerant than Indians.

Table 5-29: Mann-Whitney U Test for Indian and White Respondents

	Risk Tolerance Score
Mann-Whitney U	5250.000
Wilcoxon W	8571.000
Z	-.578
Asymp. Sig. (2-tailed)	.564

Table 5-30: Median Analysis for Indian and White Respondents

Race	N	Median
Indian	81	25.00
White	136	26.00
Total	217	26.00

The findings, although weak in their support for a significant relationship, are similar to the studies by Schooley and Worden (1996: 93), Barsky *et al* (1997: 550), Bellante and Green (2004: 278) and Yao *et al* (2005: 56-57) who found significant effects when analysing race. Gumede's (2009: 24 and 34) results also suggested that Whites were more risk tolerant than Blacks, Asians/Indians and Coloureds. The fact that only the Indian category was found to be significant was interesting as the sample used in this study was much larger and more diverse than those used in the Gumede (2009) and Strydom *et al* (2009) study and therefore, the problem of homogeneity experienced by these studies was avoided. The use of a different instrument in this study may be linked to the difference in findings, particularly in comparison with the Strydom *et al* (2009) study. This suggests further research is necessary.

Results from the univariate regressions using Black first and then White as the reference category, proved that none of the categories were statistically significant and therefore, race had no effect on risk tolerance levels in these models. The regression results can be found in Tables 5-31 and 5-32 below. Both models were insignificant based on the results for the Omnibus Test of Model Coefficients (in both cases the models' χ^2 statistics had a $p = 0.537$ which is greater than 0.05), however, the more reliable

Hosmer and Lemeshow test (Pallant, 2007: 174) produced test statistics (1.000 for both) that suggested a good fit.

Table 5-31: Univariate Binary Logistic Model with Race (ref. category = Black)

	B	S.E.	Wald	df	*p*	Odds Ratio
Black			2.159	3	.540	
Coloured	-.488	.415	1.382	1	.240	.614
Indian	-.439	.335	1.720	1	.190	.644
White	-.275	.303	.825	1	.364	.760
Constant	.216	.250	.751	1	.386	1.241

Table 5-32: Univariate Binary Logistic Model with Race (ref. category = White)

	B	S.E.	Wald	df	*p*	Odds Ratio
White			2.159	3	.540	
Black	.275	.303	.825	1	.364	1.317
Coloured	-.213	.374	.325	1	.568	.808
Indian	-.164	.282	.340	1	.560	.848
Constant	-.059	.172	.118	1	.732	.943

5.3.3.6 Household Income and Risk Tolerance

In order to determine whether there was a significant relationship between income and risk tolerance, hypothesis six was tested as follows:

H_0: $\beta_6 = 0$

H_1: $\beta_6 \neq 0$

The results shown in Table 5-13 suggest that income had a significant effect on risk tolerance for those respondents who fell in the lowest (less than R150 000) and the fifth (greater than R455 001 but less than R580 000) income category. The lowest category had a Wald statistic of 9.523 which was high and significant at the ten percent level (p = 0.090) and the fifth category had a Wald statistic of 3.582 which was also significant at the ten percent level (p = 0.058). The positive β value of 1.575 and an odds ratio greater than one (4.831) suggest that those respondents in the fifth category are significantly more risk tolerant than those in the lowest category. This finding suggests that the null hypothesis can be rejected and therefore, $\beta_6 \neq 0$.

This relationship could be plausible as it shows that household income plays an important role in determining risk tolerance for the lowest income category where individuals may be less willing to take more risks as they do not have as much disposable income to play around with. On the other hand, as a respondent moves into the second, third and fourth categories income does not play a significant role in determining risk tolerance levels. However, a respondent that falls into the second highest category could be more willing to take on risk as they have the money to spare in the event of a loss, whilst those in the highest category may not base their decisions on income as they have a large amount at their disposal. A similar finding to this was found by Morin and Suarez (1983: 1210) who, when dividing respondents into lower wealth (\$1 - \$12 500) and upper wealth (\$12 500 - \$100 000), found that those in the upper wealth group showed a trend of decreasing risk aversion. This lends support to the notion that risk tolerance is positively related to income but further investigation is needed, particularly with regards to the middle income categories. When examining the univariate regression with the income categories the same results were found as shown in the table below. It stands to reason, therefore, that the null hypothesis that there is no difference in risk tolerance across income brackets can be rejected.

Table 5-33: Univariate Binary Logistic Model with Household Income

	B	S.E.	Wald	df	*p*	Odds Ratio
Income(1)			11.120	5	.049	
Income(2)	-.284	.284	1.000	1	.317	.753
Income(3)	.068	.338	.041	1	.839	1.071
Income(4)	.727	.452	2.591	1	.107	2.069
Income(5)	2.349	1.068	4.834	1	.028	10.475
Income(6)	.663	.545	1.478	1	.224	1.940
Constant	-.152	.175	.756	1	.385	.859

The finding that income does have a significant effect (it is noted that this is only for the first and fifth categories) on risk tolerance is consistent with the studies by Morin and Suarez (1983: 1210), Grable and Lytton (1999b: 6), Hartog *et al* (2000: 14) and

Christiansen *et al* (2009: 8). The study by Gumede (2009: 28-29 and 38) found that income had a positive effect on risk tolerance but there was no significant relationship. Strydom *et al* (2009: 18) also found that there was no significant relationship but acknowledged that responses to their income question were extremely poor which made their findings questionable. Similar to the results found for education there is some evidence of multicollinearity as the results from the univariate analysis suggest that the first and fifth income categories are even more significant compared to the full multivariate model results.

It must be noted that some limitations arose in investigating the relationship between income and risk tolerance. Firstly, the majority of respondents (67.6 percent) fell into the two lowest income categories and this may have affected the results as individuals with lower incomes face tight budgetary constraints and are more concerned about housing and personal property and therefore, may not have the capacity to invest and take on levels of higher risk. Secondly, the income categories used were taken from the South African Revenue Services (SARS) guidelines for individual income tax (SARS, 2011) and were used as a measure for household income (combined income of all income earners in the household) which poses some concerns. People are sometimes unaware of their annual incomes as they need to take into account factors such as their salaries, interest income, dividend income and rent income, to list some examples. This necessitates a rough estimate, however, these could be wrong and therefore, impact on the results obtained. In many cases respondents are also unsure of their parents', spouses or partner's annual income and therefore, may have only recorded their own income levels in the questionnaire. The study by Gumede (2009: 14) it could be argued used a more sophisticated approach to measuring household income whereby, it was determined by asking questions from an expenditure perspective. The rationale behind this was that increased levels of household expenditure generally translate into a higher socioeconomic or financial position (Gumede, 2009: 14). This method was chosen by Gumede (2009: 14) so as to overcome the problems experienced in the Strydom *et al* (2009: 19) study which asked a direct income question in similar fashion to this study. The fact that Gumede (2009: 28-29 and 38), using an improved income measure, found no significant relationship raises some concerns and it is suggested that further research with a well defined and more accurate measure of income or wealth is recommended for further research purposes.

5.3.3.7 Religion and Risk Tolerance

The seventh hypothesis tested in the study was whether religion had any significant effect on risk tolerance and is shown below.

H_0: $\beta_7 = 0$

H_1: $\beta_7 \neq 0$

All of the religion categories were highly insignificant and generally had low Wald statistics in the full multivariate model results shown in Table 5-13. The Wald statistic for Christians was 1.822 and the *p*-value was 0.769, whilst for Hindus they were 0.149 and 0.699 respectively. Muslims had a Wald statistic of 1.351 and a *p*-value of 0.245, for Jewish respondents they were 0.000 and 1.000 respectively and for the category "Other" they were 0.444 and 0.505 respectively. From these results it can be concluded that one cannot reject the null hypothesis that religion has no effect on risk tolerance and thus, $\beta_7 = 0$. These results may have occurred due to the low numbers in some of the categories, for example there was only one Jewish respondent. Another full regression was run where only the religious categories Christian, Hindu and Muslim were included and again high *p*-values were obtained (these results can be seen in Table 5-34) and therefore, the same conclusion that religion has no effect on risk tolerance was drawn.

These results were in contrast to the studies by Barsky *et al* (1997), Halek and Eisenhauer (2001) and Hartog *et al* (2002) who found evidence that religion did have an effect on risk tolerance levels. Strydom *et al* (2009: 18) found that Christians were the least risk tolerant compared to Muslims and Hindus, respectively, but cautioned against their results as they could not control for the effects of race in their study and acknowledged that there was an overlap between race and religion as discussed in section 3.2.2.1. Gumede (2009: 26) also found that religion had no significant effect on subjective risk tolerance.

Table 5-34: Binary Logistic Model 3 with re-coded Religion Variable

	B	S.E.	Wald	df	*p*	Odds Ratio
Age	-.020	.009	5.094	1	.024	.980
Female	-.542	.258	4.428	1	.035	.581
Education(1)			3.547	2	.170	
Education(2)	-.439	.294	2.229	1	.135	.645
Education(3)	.101	.361	.078	1	.780	1.106
Black			2.968	3	.397	
Coloured	-.147	.482	.093	1	.760	.863
Indian	-.584	.527	1.230	1	.267	.558
White	.226	.365	.383	1	.536	1.253
Income(1)			10.519	5	.062	
Income(2)	-.196	.319	.379	1	.538	.822
Income(3)	.021	.380	.003	1	.955	1.022
Income(4)	.810	.493	2.698	1	.100	2.248
Income(5)	2.389	1.093	4.777	1	.029	10.905
Income(6)	.838	.602	1.938	1	.164	2.311
Single			3.928	2	.140	
Married	.158	.319	.244	1	.621	1.171
Divorced	-.974	.609	2.560	1	.110	.377
Christian			1.171	2	.557	
Hindu	.201	.573	.123	1	.725	1.223
Muslim	.743	.698	1.135	1	.287	2.103
Constant	1.068	.433	6.081	1	.014	2.909

Univariate analysis of the variable Religion confirms these findings as the categories are again all statistically insignificant (see Table 5-35 below). These results suggest one cannot reject the null hypothesis that there is no difference in risk tolerance across religious groups. It is not entirely surprising that the results were inconclusive as a category such as Christian is an extremely broad one, considering the number of different denominations a respondent could belong to, and it may be more prudent to better define this variable and the categories in future research.

Table 5-35: Univariate Binary Logistic Model with Religion

	B	S.E.	Wald	df	*p*	Odds Ratio
Christian			.826	2	.662	
Hindu	-.241	.354	.462	1	.497	.786
Muslim	.282	.519	.296	1	.587	1.326
Constant	-.031	.125	.062	1	.803	.969

Further investigation of the relationship between religion and risk tolerance was conducted by analysing whether there were any differences in risk tolerance across the religious categories but for the Indian respondents. The inconclusive results with regards to the effects religion had on risk tolerance, exhibited above, made it worthwhile to examine the subsample of Christian respondents to determine whether race had any effect on risk tolerance for this subsample. The reason for choosing the Christian category is that there was a good spread of respondents in terms of race in the Christian category as shown in the table below.

Table 5-36: Race Statistics for Christian Respondents

		Christian	Total
Race	Black	62	62
	Coloured	37	37
	Indian	28	28
	White	131	131
Total		258	258

The results from the univariate Binary Logistic model for the Christian subsample are shown below. As can be seen none of the race categories are significant judging by their *p*-values suggesting that race plays no role in determining risk tolerance levels for Christians.

Table 5-37: Univariate Binary Logistic Model with Race (for Christian respondents)

	B	S.E.	Wald	df	*p*	Odds Ratio
Black			2.913	3	.405	
Coloured	-.531	.419	1.607	1	.205	.588
Indian	-.695	.464	2.242	1	.134	.499
White	-.275	.310	.785	1	.376	.760
Constant	.260	.256	1.026	1	.311	1.296

Further analysis was also conducted by testing whether religion had any effect on risk tolerance for the Indian respondents in the study. The reason for choosing the Indian subsample is that the White respondents were almost all in the Christian category, Blacks were predominantly Christian and so were all Coloured respondents. There was a better spread of Indian respondents across the religion categories as shown in the table below.

Table 5-38: Religion per Race Statistics

	Indians	Blacks	Whites	Coloureds
Christian	28	62	132	37
Hindu	37			
Muslim	16			
Missing/Other		3	5	
Total	81	65	137	37

The results for the univariate model analysing the relationship between religion and risk tolerance for the Indian subsample of respondents are shown below.

Table 5-39: Univariate Binary Logistic Model with Religion (for Indian respondents)

	B	S.E.	Wald	df	*p*	Odds Ratio
Christian			1.209	2	.546	
Hindu	.163	.510	.103	1	.749	1.177
Muslim	.687	.635	1.168	1	.280	1.987
Constant	-.435	.387	1.266	1	.261	.647

As can be seen the results are no more conclusive, based on the Wald test, as previously described for the whole dataset. All the *p*-values are statistically insignificant ($p_{\text{Christian}}$ = 0.546; p_{Hindu} = 0.749 and p_{Muslim} = 0.280). A Kruskal-Wallis test and median analysis was also conducted to determine any effects, with the results shown below.

Table 5-40: Kruskal-Wallis Test for Indian Respondents

	Risk Tolerance Score
Chi-Square	1.240
df	2
Asymp. Sig.	.538

Table 5-41: Median Analysis for Indian Respondents

Religion	N	Median
Christian	28	25.00
Hindu	37	23.00
Muslim	16	27.50
Total	81	25.00

Similar to the results from the Binary Logistic model the test was insignificant (p = 0.538), however, the median analysis suggested, for Indian respondents, that Muslims had the highest risk tolerance, followed by Christians and then Hindus. Even though there was a better spread of Indian respondents across the religion categories there may still have been too few respondents in the Muslim category (16), for example, which may have affected the significance of the results in both test procedures. It is, therefore, recommended that future research aims to achieve more respondents in each of the categories, particularly the Muslim category.

Although the full multivariate Binary Logistic model estimated in Table 5-13 provided some conclusive results as to age and gender, for example, there were some concerns regarding the data. As such an amended Binary Logistic model was estimated that dealt with these problems and a discussion of this model follows. This model also served as a way of checking the robustness of the findings from the model estimated in Table 5-13.

5.3.4 Amended Binary Logistic Model

As mentioned, certain concerns arose during the estimation of the first model in Table 5-13 particularly with regards to the number of observations in certain categories, the appropriateness of certain variables given their significance values and the presence of outliers. For these reasons it was decided that the income categories "greater than R325 001 but less than R455 000", "greater than R455 001 but less than R580 000" and "greater than R580 001" should be collapsed into one category labeled "greater than R325 001". Besides some of the categories being insignificant, another reason for doing this was to account for the smaller number of respondents in the higher income categories. The variables "Religion" and "Race" were removed from the multivariate regression as the categories were all highly insignificant based on their *p*-values[8]. Finally, based on the decision criteria, used by SPSS, for outliers or cases that the model does not fit well, a respondent was excluded from the analysis as the ZResid value for this particular respondent was less than -2.5 (Pallant, 2007: 177). The results for the amended model are shown below.

The second model estimated produced even more satisfactory goodness of fit statistics, compared to those for the model estimated in Table 5-13, providing support for the model. The model was statistically significant, χ^2 (9, N = 314, $p < 0.05$ [$p = 0.001$]) indicating that the model was able to distinguish between respondents who were above or below average risk tolerant. The Hosmer and Lemeshow Test was 2.749 and had a significance level of 0.949 which is much larger than the required value of 0.05 therefore, providing further support for the model. Another important observation was that there were no outliers in the amended model. The relationships between each of the explanatory variables and risk tolerance in the amended model are discussed next.

[8] Amended models were estimated that included race and religion separately however, the variables were still highly insignificant and therefore, both variables were omitted.

Table 5-42: Amended Binary Logistic Model[9]

	B	S.E.	Wald	df	*p*	Odds Ratio
Age	-.015	.008	3.435	1	.064	.985
Female	-.445	.241	3.424	1	.064	.641
Education(1)			2.695	2	.260	
Education(2)	-.288	.279	1.066	1	.302	.750
Education(3)	.218	.345	.400	1	.527	1.244
Single			3.800	2	.150	
Married	.076	.300	.065	1	.799	1.079
Divorced	-1.027	.595	2.979	1	.084	.358
IncomeRec(1)			10.408	3	.015	
IncomeRec(2)	-.212	.302	.494	1	.482	.809
IncomeRec(3)	.057	.370	.024	1	.878	1.058
IncomeRec(4)	1.031	.389	7.013	1	.008	2.803
Constant	.747	.381	3.838	1	.050	2.111

5.3.4.1 Age and Risk Tolerance in the Amended Model

The results from the amended model presented above show that age was significant at the ten percent level ($p = 0.064$), whilst in the full model (Table 5-13) it was significant at the five percent level ($p = 0.041$) according to the Wald test. The relationship between age and risk tolerance is the same, however, in that there they are negatively related to one another. The β value in this model was -0.015 and the odds ratio was below one (0.985). This finding provides further evidence that age does influence individual risk tolerance and one can reject the null hypothesis ($\beta_1 = 0$) that age has no effect on risk tolerance. However, it is interesting that although the goodness of fit statistics for this model were improved, age was less significant. A possible reason for this could be linked to the refined income variable in that age could be capturing some of the effects of income whereby, older respondents, who are employed, are more likely to have higher incomes as they have been working for longer, for example. This obviously does not apply to those who are retired, generally over the age of 65, and are drawing a small annual pension. The following table shows the relationship between the age categories and the re-coded income categories.

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[9] In this model the categories of IncomeRec, IncomeRec(1), IncomeRec(2) and IncomeRec(3) represent the income categories of <R150 000, R150 001<R235 000, R235 001<R325 000 and >R325 001, respectively, for the re-coded income variable. The same ordering applies to further models which include the re-coded income variable.

Table 5-43: The Relationship between Age and Income (re-coded)

		Income				
		<R150 000	R150 001 <R235 000	R235 001 <R325 000	>R325 001	Total
Age	17<25	50	10	10	7	77
	26<35	22	21	12	12	67
	36<45	10	21	10	11	52
	46<65	28	26	13	20	87
	66<100	21	6	3	1	31
Total		131	84	48	51	314

The table shows that the majority of the respondents in the 17 to 25 age group were in the less than R150 000 income category whilst there were only 28 respondents from the 46 to 65 age group in the lowest income category. In comparison, there were 20 respondents in the highest income category who were in the 46 to 65 age group and only seven 17 to 25 year olds in this income category. Therefore, the change in significance may be attributed to this.

5.3.4.2 Gender and Risk Tolerance in the Amended Model

Gender was found to be a significant determinant in the first Binary Logistic model and was also significant, but at the ten percent level (p = 0.064), in the amended model with a Wald statistic of 3.424. The β value of -0.445 indicates that female respondents are less likely to fall in the above average risk tolerance category (the odds ratio of 0.641 confirmed this). This result provides further support for the notion that gender has a significant effect on risk tolerance levels (i.e. $\beta_2 \neq 0$). Similar to that of age though, gender is less significant in this model. The first model produced a p-value of 0.021 for gender. Again this result may be linked to the refined income variable as it appears that in each re-coded income category a higher percentage of the respondents were males as shown in the table below.

Table 5-44: The Relationship between Gender and Income (re-coded)

		Gender		
		Male	Female	Total
Income	<R150 000	70	62	132
	R150 001<R235 000	45	39	84
	R235 001<R325 000	28	20	48
	>R325 001	27	24	51
Total		170	145	315

5.3.4.3 Education and Risk Tolerance in the Amended Model

In the second model the *p*-value for Matric or less was 0.260 (Wald statistic = 2.695), the education category 3 Year Undergraduate Degree/Diploma or less (but higher than Matric) produced a $p = 0.302$ (Wald statistic = 1.066), whilst for the category Postgraduate Degree $p = 0.527$ (Wald statistic = 0.400). All these *p*-values are statistically insignificant and therefore, offer no improvement on the results from the model estimated in Table 5-13 providing further support that one cannot reject the null hypothesis that education level has no effect on risk tolerance.

5.3.4.4 Marital Status and Risk Tolerance in the Amended Model

Results from the amended model for marital status were interesting in that being divorced had a significant effect (below the ten percent level) on risk tolerance. One will remember that the full multivariate model suggested that the effect was borderline at the ten percent level. The Wald statistic of 2.979 was significant at the ten percent level ($p = 0.084$). However, being single or married still had no significant effect on risk tolerance levels. The second model produced *p*-values of 0.150 and 0.799 and Wald statistics of 3.800 and 0.065, respectively, for each category. The β value for the divorced category was -1.027 suggesting that being divorced decreases one's risk tolerance level (the odds ratio of 0.358 was below one as well) with the reasoning being similar to that provided in section 5.3.3.4. This suggests that, in this model, one could reject the null hypothesis.

5.3.4.5 Income and Risk Tolerance in the Amended Model

As already mentioned the original six income categories were collapsed into four categories for the estimation of the amended model. The results provided implied that the first category (annual incomes less than R150 000) and the fourth (annual incomes greater than R325 001) were significantly related to risk tolerance whilst the other two were not. The first category was significant at the five percent level (p = 0.015 with a Wald statistic of 10.408), whilst the fourth was significant at the one percent level (p = 0.008 with a Wald statistic of 7.013). The β value of 1.031 and the odds ratio greater than one (2.803) suggest that there is a positive relationship between income and risk tolerance, for a respondent who falls in the highest category. This suggests that, in this model $\beta_5 \neq 0$ and the null hypothesis could be rejected.

As mentioned in the methodology of this study, the SCF question was also included in the questionnaire. This was done so that a comparison between the results from the Grable and Lytton (1999a) questionnaire and the SCF question results could be made and hence could act as a test of the robustness of the former instrument's result. It was noticed while collating the study data that some respondents' choices for the SCF question did not match up with their scores from the Grable and Lytton (1999a) questionnaire (i.e. some who chose either of the two more risky options in the SCF question scored low in the questionnaire). As has already been discussed, Grable and Lytton (1999a: 178) also tested the validity of their instrument against the SCF question and concluded that the 13 item risk assessment tool measured a wider variety of financial risk components compared to a single item such as the SCF question. Therefore, interesting results were expected and these are discussed next.

5.3.5 A Comparison of the Results from the Grable and Lytton (1999a) Questionnaire and the SCF Question

In order to draw a comparison with the results from the Grable and Lytton (1999a) questionnaire the responses to the SCF question were re-coded into two categories so that a Binary Logistic model could be estimated. The options of substantial financial risks expecting to earn substantial returns and above average financial risks expecting to earn above average returns were combined into one category indicating a substantial/above average risk tolerance. The other two options, average financial risks expecting to earn average returns and no financial risks, were combined into the category "average/no financial risks". A full multivariate model was estimated and included the re-coded education and religion categories, previously discussed, and the results are shown in Table 5-45 which is presented over the page. In terms of goodness of fit, the model was significant at the five percent level ($p = 0.000$) and the Hosmer and Lemeshow Test of 3.982 had a significance level of 0.859 which is larger than the required value of 0.05 therefore, indicating that the model had a good fit.

The results shown in Table 5-45 are particularly interesting with respect to race and income as will be discussed. Age and gender are, similar to previous findings from the Grable and Lytton (1999a) questionnaire, statistically significant (at the ten percent level). The findings again suggest that risk tolerance decreases with age and that females are less risk tolerant than males. Education, marital status and religion were all found to be insignificant, similar to the Grable and Lytton (1999a) findings. In terms of race the results are quite different. The findings shown in Table 5-13 indicated that race was insignificant, however, Table 5-45 shows that, in contrast only the category for Coloured respondents was insignificant for the SCF question results. The other three categories (Black, Indian and White) were all significant at the five percent level with the results suggesting that Blacks (the reference category) were more risk tolerant than Indians as well as Whites.

The results for income are also in stark contrast to the previous findings by Grable and Lytton (1999a). In the latter case income was found to only be significant for two of the categories, even when re-coded, whereas the output in the table below suggests that all the categories but the second (greater than R150 001 but less than R235 000) were significantly related to risk tolerance. The β values show that as income increases risk tolerance increases as those who fell into the first category (less than R150 000) were the least risk tolerant compared to each of the rest of the categories.

Table 5-45: Binary Logistic Results with SCF Question

	B	S.E.	Wald	df	*p*	Odds Ratio
Age	-.019	.010	3.396	1	.065	.981
Female	-.475	.272	3.048	1	.081	.622
Education(1)			1.309	2	.520	
Education(2)	-.329	.320	1.054	1	.305	.720
Education(3)	-.373	.386	.935	1	.334	.689
Black			9.727	3	.021	
Coloured	-.514	.488	1.106	1	.293	.598
Indian	-1.733	.644	7.244	1	.007	.177
White	-.881	.375	5.511	1	.019	.414
Single			1.346	2	.510	
Married	-.377	.351	1.155	1	.283	.686
Divorced	-.502	.598	.706	1	.401	.605
Income(1)			15.777	5	.008	
Income(2)	.481	.355	1.835	1	.176	1.617
Income(3)	1.021	.413	6.114	1	.013	2.776
Income(4)	1.573	.510	9.514	1	.002	4.823
Income(5)	1.361	.745	3.343	1	.067	3.901
Income(6)	1.759	.611	8.277	1	.004	5.804
Christian			2.690	2	.261	
Hindu	1.114	.681	2.680	1	.102	3.047
Muslim	.718	.803	.800	1	.371	2.051
Constant	.884	.457	3.741	1	.053	2.420

The difference in findings is interesting and provides reason to question which of the two instruments is the most appropriate. Firstly, the SCF question measures risk tolerance at a level that could be construed as being crude and superficial, with only one question. Furthermore, it is possible that respondents may be drawn to the higher risk options by the mere fact that they are associated with higher returns and the risks involved are not fully understood. The study by Yang (2004: 21) commented that the SCF question has its limitations in that it only serves as a measure of a person's attitudes towards risk. It also does not determine whether individuals are prepared to incur investment risk in equities, bonds or mutual funds, for example, and whether risk appetites change when faced with losses or gains. Furthermore, Yang (2004: 21) stated that the word "substantial" may be interpreted differently by different people. The use of the more in-depth Grable and Lytton (1999a) questionnaire which tends to ask more probing questions may then be discovering discrepancies in a person's grasp of the concept of financial risk. On the other hand there may also be problems with the use of the Grable and Lytton (1999a) questionnaire. Possibly a South African specific version needs to be developed or research should be focused on people who have an improved level of knowledge or understanding of investing and financial risks. These problems provide ideal scope for further research in this field.

Over and above the models and tests conducted above an additional model was estimated in order to determine whether there were any interaction effects between gender and education on risk tolerance.

5.3.6 The Effect of Gender and Education on Risk Tolerance

As described in the methodology chapter a quota sampling technique was used, with education and gender as the two quotas, when gathering the data. It therefore makes sense to analyse whether there was any difference in the results when examining the male and female subsamples. As can be seen in the two tables presented below, the results suggest that splitting the data up into two subsamples for males and females respectively, has no impact and none of the variables were significant using the Wald test.

Table 5-46: Univariate Binary Logistic Model with Education (for males)

	B	S.E.	Wald	df	*p*	Odds Ratio
Education(1)			1.197	2	.550	
Education(2)	-.129	.345	.140	1	.708	.879
Education(3)	.323	.426	.573	1	.449	1.381
Constant	.129	.255	.258	1	.612	1.138

Table 5-47: Univariate Binary Logistic Model with Education (for females)

	B	S.E.	Wald	df	p	Odds Ratio
Education(1)			4.196	2	.123	
Education(2)	-.216	.380	.323	1	.570	.806
Education(3)	.726	.461	2.479	1	.115	2.066
Constant	-.377	.265	2.027	1	.155	.686

In addition to the Binary Logistic models estimated examining the relationship between the overall concept of financial risk tolerance and certain demographic characteristics further analysis was conducted by deconstructing the Grable and Lytton (1999a) instrument into its three principal components of investment risk; risk comfort and experience; and speculative risk. The findings from this procedure are discussed next.

5.3.7 The Relationship between Demographic Factors and Investment Risk; Risk Comfort and Experience; and Speculative risk

As discussed in the methodology of this study, the Grable and Lytton (1999a) instrument measured a variety of different dimensions of risk which, when combined, provided an appropriate measure of the overall concept of financial risk (Grable and Lytton, 1999a: 173). Furthermore, the dimensions measured financial risk tolerance using the three constructs of investment risk, risk comfort and experience and speculative risk (Grable and Lytton, 1999a: 177). These constructs have already been explained in chapter four discussing the methodology of this study. Therefore, as an extension to this study it was decided to test whether there were any significant relationships between the demographic factors and the three constructs measured by the instrument. Each construct was regressed against age, gender, the re-coded education variable, race, the re-coded income variable, marital status and the three religion categories. The results are discussed below.

5.3.7.1 Investment Risk

In terms of investment risk the maximum score a respondent could obtain for the five questions (see section 4.4) was 17 with a minimum of five. Results showed that the mean score was 9.84 and therefore, all respondents with a score above this were classified as having an above average investment risk tolerance. Those that scored below 9.84 were considered below average. The model for investment risk produced goodness of fit statistics that indicated the model was reliable [the model was significant at the five percent level (p = 0.000) and the Hosmer and Lemeshow Test had a significance level of 0.727]. The most striking findings compared to those when analysing the overall concept of financial risk were that gender was no longer significant, the category for Coloureds was significant and all the categories for marital status were as well. Table 5-48 below presents these results. The fact that gender had no significant effect suggests that the way that males and females control their emotions when investing has no effect on their tolerance of investment risk. However, it appears that emotions have an effect for Coloured respondents who appear to be more willing to take on direct investment risks compared to the reference category of being Black. The findings for marital status suggest that both married and divorced respondents are significantly less tolerant of investment risk than single respondents. This could be true as single respondents are often not accountable to a spouse or dependents (it is acknowledged that some single respondents may have partners or dependents and therefore, this is merely suggestive) and can therefore, take on more direct investments and consider the needs or emotions of others.

Similar to the findings shown in Table 5-13 for the overall concept of financial risk tolerance, age was significant and negatively related to investment risk and the highest income category and lowest income category were significant. Respondents in the highest category exhibited a higher tolerance for investment risk. The findings for risk comfort and experience are discussed next.

Table 5-48: Investment Risk Binary Logistic Model

	B	S.E.	Wald	df	*p*	Odds Ratio
Age	-.023	.009	6.833	1	.009	.977
Female	.061	.263	.054	1	.816	1.063
Education(1)			1.756	2	.416	
Education(2)	.165	.293	.315	1	.574	1.179
Education(3)	.492	.372	1.752	1	.186	1.636
Black			3.480	3	.323	
Coloured	.835	.493	2.867	1	.090	2.306
Indian	.361	.526	.469	1	.493	1.434
White	.600	.380	2.492	1	.114	1.822
IncomeRec(1)			8.012	3	.046	
IncomeRec(2)	.112	.328	.117	1	.733	1.119
IncomeRec(3)	.627	.402	2.428	1	.119	1.871
IncomeRec(4)	1.052	.409	6.612	1	.010	2.865
Single			11.605	2	.003	
Married	-.754	.325	5.369	1	.020	.470
Divorced	-1.968	.614	10.269	1	.001	.140
Christian			1.854	2	.396	
Hindu	-.391	.575	.462	1	.497	.677
Muslim	.523	.713	.538	1	.463	1.687
Constant	.671	.429	2.450	1	.118	1.956

5.3.7.2 Risk Comfort and Experience

Respondents could score a maximum of 20 and a minimum of five over the five questions dealing with risk comfort and experience (see section 4.4). The sample mean for these questions was 10.16 and thus, respondents scoring below this were categorised as being below average in terms of risk comfort and experience and those who scored above 10.16, above average. The results for the relationship between the demographic factors and risk comfort and experience are shown in Table 5-49, however, the goodness of fit statistics were inconclusive and possibly suggested a poor fit of the data. The Omnibus Test of Model Coefficients produced a χ^2 statistic of 30.460 with p = 0.007 which is acceptable, however, the Hosmer and Lemeshow statistic of 16.963 and p = 0.030 was insignificant. These results suggest no inferences can be made from the model as according to Pallant (2007: 174) the Hosmer and Lemeshow test is the most reliable. A possible reason for these results could be that many of the respondents were not familiar or comfortable with investing and therefore, provided inconclusive findings. This could be linked to the large number of respondents that fell into the two lowest income categories and therefore, the majority of respondents have little opportunity to gain experience and become more comfortable with investing and its associated risks. Nevertheless, it must be noted that age was still significantly related and negative and three of the four income categories were also significant. The findings for speculative risk are discussed next.

Table 5-49: Risk Comfort and Experience Binary Logistic Model

	B	S.E.	Wald	df	*p*	Odds Ratio
Age	-.028	.010	8.343	1	.004	.973
Female	-.146	.258	.320	1	.571	.864
Education(1)			2.083	2	.353	
Education(2)	-.421	.300	1.968	1	.161	.656
Education(3)	-.152	.362	.176	1	.675	.859
Black			.999	3	.802	
Coloured	-.001	.475	.000	1	.998	.999
Indian	-.485	.527	.846	1	.358	.616
White	-.146	.362	.163	1	.687	.864
IncomeRec(1)			10.330	3	.016	
IncomeRec(2)	.058	.332	.030	1	.862	1.060
IncomeRec(3)	.778	.386	4.060	1	.044	2.176
IncomeRec(4)	1.069	.393	7.412	1	.006	2.914
Single			.617	2	.735	
Married	-.038	.331	.013	1	.909	.963
Divorced	-.441	.582	.573	1	.449	.643
Christian			.444	2	.801	
Hindu	.018	.577	.001	1	.975	1.019
Muslim	-.409	.716	.327	1	.568	.664
Constant	.933	.436	4.574	1	.032	2.543

5.3.7.3 Speculative Risk

As discussed in section 4.4 only three questions measured speculative risk and respondents could score a maximum of ten and a minimum of three for these questions. The mean obtained from the sample was 6.18 suggesting that those who scored below this were below average with respect to their tolerance of speculative risk and those who scored above 6.18 were above average. The goodness of fit statistics were much improved for the speculative risk model with both the Omnibus Test of Model Coefficients (p = 0.037) and the Hosmer and Lemeshow (p = 0.810) providing significant results in support of the model's fit.

Table 5-50: Speculative Risk Binary Logistic Model

	B	S.E.	Wald	df	*p*	Odds Ratio
Age	.000	.009	.002	1	.964	1.000
Female	-.037	.257	.021	1	.884	.963
Education(1)			2.065	2	.356	
Education(2)	-.149	.294	.256	1	.613	.862
Education(3)	-.528	.373	2.011	1	.156	.590
Black			1.978	3	.577	
Coloured	-.585	.482	1.477	1	.224	.557
Indian	.099	.513	.037	1	.846	1.104
White	-.242	.364	.440	1	.507	.785
IncomeRec(1)			15.419	3	.001	
IncomeRec(2)	.396	.329	1.445	1	.229	1.485
IncomeRec(3)	.733	.385	3.623	1	.057	2.082
IncomeRec(4)	1.556	.404	14.840	1	.000	4.738
Single			.903	2	.637	
Married	-.245	.321	.584	1	.445	.782
Divorced	-.464	.560	.685	1	.408	.629
Christian			5.715	2	.057	
Hindu	-1.442	.606	5.668	1	.017	.236
Muslim	-.582	.684	.723	1	.395	.559
Constant	-.259	.430	.362	1	.547	.772

In contrast to previous findings in the study both age and gender were insignificant as the p-values shown in Table 5-50 suggest. Interestingly, only the second income category was insignificant and the Christian and Hindu categories for religion were significant. These results suggest that income and religion plays more of a role when respondents are faced with questions that require them to speculate on certain outcomes. Respondents in the third and highest income categories were significantly more likely to take on higher levels of speculative risk than those in the lowest category, whilst Hindus were significantly less likely to take on as much speculative risk as Christians based on the results shown in Table 5-50. All the other categories of the various variables were found to be insignificant.

Results from the various tests provide interesting points for discussion, however, it is acknowledged that the sample was not entirely representative of the population and therefore, the results from the various statistical methods employed cannot be used to base general assumptions regarding risk tolerance levels according to certain demographic characteristics. Regardless of this, however, important inferences can be made from the findings. Results from the various analyses conducted in this study provide further evidence that an individual’s demographic characteristics play an important role in determining their risk tolerance levels. In some cases variables had a significant effect, for example age and gender, whereas, the evidence for other variables was not always as conclusive. Still one cannot rule out the notion that subjective financial risk tolerance is influenced by these factors. It is acknowledged, however, that further research is needed particularly with regards to the impact of a respondent’s race and religion. Limitations, such as those with the sample, are discussed further in the chapter concluding this study.

6 CONCLUSION

This study provides important insight as to the determinants of individual risk tolerance levels and thus, identifies critical aspects that need to be considered in the constructing of investment portfolios. The importance of adequately measuring an individual's financial risk tolerance cannot be ignored. The implications of inaccurate assessments and face-value assumptions can be detrimental to a person's investment goals. Factors such as expected returns and investment horizons, together with a risk profile, are important considerations that need to be taken into account when making the asset allocation decision whether individually, or through a financial advisor or planner. However, the importance of risk profiles is not limited to the investment industry and can be, and has been, applied to many other fields. It has already been noted that companies wishing to ensure their employees, or prospective employees, match their overall risk profile can gain great value from properly assessing their appetites for risk.

It is obvious that the applications of risk tolerance/aversion measures are widespread but the difficulty in providing the truest assessment is compounded by the lack of consensus on the most appropriate measure to use in order to determine risk tolerance levels. Broadly speaking, it was shown that there are two ways to measure risk tolerance, either objectively or subjectively. This particular study employed the use of a subjective questionnaire in order to determine the risk tolerance levels, and how demographic factors affected these levels, of respondents in the sample, in a similar fashion to studies by Grable and Lytton (1999b), Al-Ajmi (2008), Strydom *et al* (2009) and Anbar and Eker (2010). In contrast there were studies reviewed that used objective measures such as those by Wang and Hanna (1997), Sunden and Surette (1998), Halek and Eisenhauer (2001) and Christiansen *et al* (2009). Some studies even examined both types of risk tolerance using various methods [see Chang *et al* (2004) and Jianakoplos and Bernasek (2006)].

The evidence as to how demographic factors such as age, education and race, amongst others, affect risk aversion levels appears to be mixed. Many international studies have investigated such relationships and have either found support for the previous literature or reasons to refute it. The literature reviewed from a South African context was limited to the two UKZN based studies by Strydom *et al* (2009) and Gumede (2009) who found interesting results despite some of their studies' weaknesses. One of the aims of this study was to improve on these existing South African studies by obtaining a larger sample and by using a more robust statistical analysis technique. As such the use of a Binary Logistic model formed part of the main analysis, however, non-parametric techniques were also used to draw direct comparisons with the studies by Strydom *et al* (2009) and Anbar and Eker (2010). The study sample was drawn from customers at certain shopping malls in the Pietermaritzburg area.

The findings from the full multivariate logistic regression suggested that age, gender, and some of the race and income categories significantly affected respondents' risk tolerance levels. Conversely, it was found that education and religion had no significant effect on risk tolerance, whilst some of the marital status categories (single and divorced) were marginal in terms of their insignificance and the results may be more conclusive in a bigger sample. More specifically, it was found that risk tolerance decreased with age providing further support to the life-cycle hypothesis which follows that, as an individual grows older, their risk tolerance levels decrease. The idea that younger individuals are more risk tolerant seems plausible considering that theoretically, they have longer to live and therefore, a greater period to recover losses if necessary. Younger people can also choose to forego leisure time and replace it with more work and consequently, earn more income to replace any losses from investing. An older investor, such as a retiree, does not have the option of being able to focus more time on work and therefore, may be more prudent and cautious when faced with risk. These factors could explain why a negative relationship between age and subjective financial risk tolerance was found.

With regards to gender, it was found that females exhibited a lower tolerance for risk, which is generally assumed to be the case. The finding that females favour lower levels of financial risk is not surprising given the many studies that have found similar results. However, as has been extensively discussed, financial advisors are cautioned against discriminating against females or forming heuristic based judgements and immediately assuming all females to be less risk tolerant than males. The "know your client" rule is applicable in every case and should be carefully adhered to. It is generally accepted that females have a greater longevity compared to males and therefore, have a greater need for adequate financial resources particularly in their older or retirement years. When investing, females need to be acutely aware of the potential dangers of not choosing the correct or appropriate investment products and financial advisors have an important role to play in this regard.

There was a significant difference in risk tolerance between White and Indian respondents, who were found to be less risk tolerant. The finding that there was only a significant difference in risk tolerance between Whites and Indians was surprising in the context of South Africa's history. The fact that there was no significant difference in risk tolerance levels between Black and White respondents, suggests that attributing the results to South Africa's political past is entirely wrong. This is an interesting finding and provides an ideal topic for further research.

It was found that falling in the second highest income category meant that individuals were significantly more risk tolerant than those in the lowest, which lends some support to the notion that risk tolerance is positively related to income. The finding that risk tolerance was not significantly affected by income for all the categories investigated is surprising as previous research has suggested that this should be the case. It is plausible to think that as income increases an investor's risk tolerance should increase as they have more income to spare and can therefore choose higher risk options. Alternatively, it is equally plausible to think that as an investor accumulates more income they may become more prudent in order to protect their wealth and therefore less risk tolerant. In both cases one would expect there to be a significant effect, however, the finding from this study suggests that income does not play a significant role in determining subjective risk tolerance levels for four out of the six income categories. The fact that there was no recurring relationship across the income categories provides an interesting area for further research.

The finding, for marital status, that being single or divorced was marginally insignificant at the ten percent level, is interesting considering that other studies have found more conclusive results. This suggests that this is another area which would benefit from further research and a larger sample may help in this regard. In terms of the effect education level had on risk tolerance, no meaningful conclusions could be drawn even after collapsing some of the categories. The results may have been affected by the poor definitions used for each category and suggest refinements need to be made for future research purposes. The findings for the relationship between religion and risk tolerance were inconclusive and could possibly be attributed to the very high number of respondents in one category (Christian) as opposed to the other categories.

Non-parametric test results proved that there was a significant difference in risk tolerance between males and females with males being more risk tolerant than females. Risk tolerance was found to decrease with age, similar to the findings from the Binary Logistic model, whilst education had a significant, and positive, effect on risk tolerance. There was a significant difference in risk tolerance across the income categories, and the results suggested that respondents in the highest income category were the most risk tolerant. Similar to the logistic regression results, it was found that, for marital status, single respondents were the most risk tolerant, however, race had no significant effect on risk tolerance. Furthermore, no significant differences in risk tolerance were found among the religion categories. Further analysis was also conducted, which included the examining of the relationship between the demographic factors and the three constructs (investment risk, risk comfort and experience and speculative risk) measured by the Grable and Lytton (1999a) instrument.

While it is noted that the sample used in the study was not nationally representative certain inferences can be drawn. Evidence from the study provided further support for the notion that individual financial risk tolerance is influenced by a person's demographic characteristics and therefore, it is important to bear this in mind. These findings are extremely insightful considering research of this nature is quite limited in the South African context and can be used to obtain an improved understanding and knowledge of risk tolerance and its causal factors. Ultimately, this will help in improving the financial and investment services industry and ensure that people are receiving the most appropriate and accurate advice. The results from the methodology section, using the Cronbach alpha, support the use of the Grable and Lytton (1999a) instrument and other similar questionnaires as a risk appetite assessment tool. It is, however, important to consider the continuous reassessment of risk tolerance using a subjective measure as certain demographic factors can change over time (e.g. income) and people may respond differently in certain situations and one cannot base assumptions on an observation made in a single situation.

It is acknowledged that certain limitations did arise in the research process. Firstly, the sampling process could be improved as it was evident from the statistical analysis that more respondents were needed in certain categories. In addition it was not nationally representative, thus results from the study cannot be generalised to cover the entire South African population. Furthermore, the definition of some of the demographic variables, such as income and education, may have limited the analysis in that they were too broad or not explicit enough. The use of individual income tax brackets as a measure of household income is one such limitation. Whilst, for education, there was no distinction made between having a degree or diploma, for example. With regards to the income data the overwhelming majority of respondents fell into the two lowest categories and this may have negatively impacted on the results obtained.

Over and above the conclusions drawn in this study, ideal opportunities for further research, particularly from a South African perspective, present themselves. A much larger, more representative sample is an area where improvements can be made or possibly directing research efforts towards one specific demographic factor which would allow for an improved analysis with regards to education and religion, for example. Further research is also recommended with a questionnaire developed that is applicable to South African respondents as mentioned in chapter five. Increasing the number of risk tolerance categories in order to draw a more direct comparison with results from the SCF question would also allow a researcher to employ the use of an ordered response model, possibly improving results. It would also be interesting to compare the results obtained using a probit model to those obtained (using the logit model) in this study. One could also use the Arrow-Pratt approach in conjunction with a subjective questionnaire and determine whether there are any discrepancies. It is also recommended for future research that the definitions of the various factors' categories are greatly improved, most notably with respect to income and education, or assessed in a different way. In addressing the issue of having a high concentration of respondents in the lower income brackets, it would also be beneficial to conduct further research in an area that is, on average, more affluent than the sample obtained in this study.

Another very interesting area for further research would be to access a sample of clients of a financial advisory firm and administer the questionnaire used in this study to them, the purpose being to discern whether the same risk profiles are obtained. The findings from this procedure would help in determining whether clients are being accurately assessed and profiled and therefore, if they are receiving the best advice and investing in the correct products.

Overall, the study does provide further evidence that, in line with international research, there is an important relationship between individual subjective financial risk tolerance levels and demographic factors. The implications of this for financial advisors and other practitioners alike, are that assessments of risk tolerance levels cannot be formed based purely on heuristics and the concept of statistical discrimination should be avoided at all costs. The importance of the "know your client" rule when advising investors cannot be ignored. Therefore, it is strongly recommended that practitioners strictly adhere to this and similar guidelines to avoid any misclassification errors. The findings also provide new evidence from a South African perspective for fellow researchers. The limitations that arose during the study provide ideal opportunities for further research together with the other areas which were suggested. The fact that there is very little South African related research of this nature when compared to international literature, advocates the continual need to provide new evidence in this field which could add significant value to the investment services industry, as an example, as well as many other industries where financial risk tolerance is an important factor.

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APPENDIX A – SUMMARY TABLE OF STUDIES REVIEWED

Table A-1: Summary Table of Studies Reviewed

Author(s)	Year	Variable(s)	Risk Tolerance Measure	Method of Analysis
Al-Ajmi	2008	Age, Income and Gender	Subjective risk tolerance assessment questionnaire	Univariate analysis and Analysis of covariance
Anbar and Eker	2010	Age	Grable and Lytton (1999a) subjective risk tolerance assessment questionnaire	Logistic regression, t-tests and ANOVA
Bajtelsmit and Bernasek	1996	Gender	Review of previous literature on gender differences in investing	
Bajtelsmit, Bernasek and Jianakoplos	1999	Gender	Arrow-Pratt relative risk aversion measure	Probit and maximum likelihood estimation; Heckman's (1979) two-step procedure to eliminate sample selection bias
Bernasek and Shwiff	2001	Gender	Analysis of percentage allocation of DC pension to stocks	Two-limit Tobit estimation
Barber and Odean	2001	Gender and Marital Status	Analysis of common stock investments	Analysis of portfolio performance and turnover rates
Barsky, Juster, Kimball and Shapiro	1997	Religion	4 ranked risk aversion categories based on lifetime income gambles	Latent variable model (cardinal preference parameter)
Bellante and Green	2004	Race and Education	Arrow-Pratt relative risk aversion measure	OLS estimation
Bertaut	1998	Wealth	Examination of household stockholding behaviour	Bivariate probit model
Chang, DeVaney and Chiremba	2004	Education	Objective risk tolerance - ratio of risky assets to net worth; Subjective risk tolerance - SCF risk tolerance question	Objective risk tolerance – Tobit model; Subjective risk tolerance – OLS estimation; Chi-square analysis
Charness and Gneezy	2007	Gender	Investment games played as a computer experiment	Binomial test
Chaulk, Johnson and Bulcroft	2003	Marital Status	Two subjective risk tolerance measures	Regression analysis in the form of a SAS Macro

Table A-2: Summary Table of Studies Reviewed (continued)

Author(s)	Year	Variable(s)	Risk Tolerance Measure	Method of Analysis
Christiansen, Joensen and Rangvid	2009	Income and Marital Status	Examination of financial market participation; Calculation of the value of stocks divided by financial wealth and total wealth	Bivariate probit model
Cohn, Lewellen, Lease and Schlarbaum	1975	Income	4 ranked risk aversion categories	Regression Analysis, Multiple discriminant analysis, Chi-square contingency analysis and AID
Coleman	2003	Gender	SCF risk tolerance question	Univariate and multivariate (logistic regression) analysis
Dwyer, Gilkeson and List	2002	Gender	Examination of purchases of types of mutual funds	Latent variable regression (ordered probit model)
Donkers, Mellenberg and Van Soest	2001	Education	8 Lottery questions to categorise respondents	Semiparametric model and structural or parametric model
Eckel and Grossman	2002	Gender	Zuckerman Sensation-Seeking Scale and Gamble choices	Log-linear models; Epps-Singleton tests; pairwise means tests
Embrey and Fox	1997	Gender and Income	SCF risk tolerance question	Multivariate analysis using a Tobit model
Faff, Mulino and Chai	2008	Gender	Lottery experiment	Univariate and multivariate empirical analysis
Friend and Blume	1975	Age	Variant of Arrow-Pratt relative risk aversion measure	Simple regressions and regressions with dummy variables
Gilliam, Goetz and Hampton	2008	Marital Status	SCF risk tolerance question	Pairwise comparison; paired-sample t-tests and repeated measure General Linear Model
Grable and Joo	2004	Education	Five Likert-type items from which scores were summated for the respondents	OLS multiple regression analysis
Grable and Lytton	1999b	Age and Income	Subjective risk tolerance assessment questionnaire	Discriminant analysis
Gumede	2009	Age, Education, Income, Race, Gender and Religion	Questionnaire similar to Strydom *et al* (2009)	Odv regression

Table A-3: Summary Table of Studies Reviewed (continued)

Author(s)	Year	Variable(s)	Risk Tolerance Measure	Method of Analysis
Halek and Eisenhauer	2001	Religion	Arrow-Pratt coefficient of relative risk aversion	Multivariate regression analysis
Hallahan, Faff and McKenzie	2004	Age, Wealth, Gender and Marital Status	Psychometric attitude test used to generate a Risk Tolerance Score	Hierarchical regression analysis
Hanna, Gutter and Fan	2001	Age	Improved version of Barsky *et al* (1997) instrument and SCF risk tolerance question	Data comparisons
Hanna and Lindamood	2004	Gender	Income gambles (pension choice measure) and SCF risk tolerance question	Correlation and regression analysis
Hanna and Lindamood	2005	Marital Status	SCF risk tolerance question	Logit model
Hartog, Ferrer-i-Carbonell and Jonker	2000	Income and Wealth, Gender and Marital Status	Arrow-Pratt coefficient of relative risk aversion	OLS estimation and the Heckman two-step method using Maximum Likelihood estimation
Hartog, Ferrer-i-Carbonell and Jonker	2002	Religion	Same as above	
Hawley and Fujii	1994	Marital Status	SCF risk tolerance question	Ordered logit model
Jianakoplos and Bernasek	2006	Age	Ratio of risky assets to wealth (Arrow-Pratt) and SCF risk tolerance question	Maximum likelihood Tobit and probit regression
Kimball, Sahm and Shapiro	2007	Education	Hypothetical lifetime income gamble choices	Maximum-likelihood methods
Lugovskyy and Grossman	2007	Gender	Psychological survey measure of risk attitudes; A gamble choice with substantial financial stakes and a prediction of others' gamble choice	Analysis of means and ordered probit models
Morin and Suarez	1988	Age and Wealth	Arrow-Pratt coefficient of relative risk aversion	OLS estimation
Olivares, Diaz and Besser	2008	Gender	Analysis of a selection of pension funds	Probit model
Pålsson	1996	Income and Gender	Arrow-Pratt coefficient of relative risk aversion	OLS estimation

Table A-4: Summary Table of Studies Reviewed (continued)

Author(s)	Year	Variable(s)	Risk Tolerance Measure	Method of Analysis
Powell and Ansic	1997	Gender	Computer experiment using realistic financial decisions	Repeated measures ANOVA and Wilcoxon tests
Riley and Chow	1992	Race, Income, Marital Status and Education	Ratio of risky assets to wealth (Arrow-Pratt)	Regression using dummy variables
Sahm	2007	Race	Hypothetical gambles over lifetime income to measure risk preference using Arrow-Pratt model	Maximum-likelihood estimation
Schubert, Brown, Gysler and Brachinger	1999	Gender	Experimental design asking investment, insurance, gain-gambling and loss-gambling questions	Regression analysis – Generalised Least Squares
Schooley and Worden	1996	Age, Race, Wealth and Education	Arrow-Pratt coefficient of relative risk aversion	Univariate and multivariate regression analysis
Strydom, Christison and Gokul	2009	Gender, Race, Religion and Wealth	Variant of Hanna and Lindamood (2004) questionnaire and SCF risk tolerance question	Nonparametric techniques
Sunden and Surette	1998	Gender and Marital Status	Asset allocation in DC Plans	Multinomial logit and probit models
Subedar, McCrae and Gerace	2006	Age	Psychometric attitude test	Univariate analysis
Sung and Hanna	1996	Education	SCF risk tolerance question	Logit model
Wang and Hanna	1997	Age	Ratio of risky assets to wealth	Heteroscedastic Tobit model
Yao, Gutter and Hanna	2005	Race, Income, Marital Status and Education	SCF risk tolerance question	Cumulative Logit model

APPENDIX B – RISK TOLERANCE QUESTIONNAIRE

Researcher: Craig Kenneth Metherell (M.Com. Student, School of Economics & Finance)
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The Impact of Demographic Factors on Subjective Financial Risk Tolerance: A South African Study.

INFORMED CONSENT

Thank you for participating in this research project, your time is greatly appreciated. It forms part of a Research Project for a Master of Commerce Degree in Finance and will prove invaluable in furthering our knowledge of the factors that impact on financial risk tolerance levels and help in developing a tool to adequately and accurately measure said level. Please note:

- **You do not have to fill in your name**
- **Data will be analysed collectively, at no time will individual responses be highlighted**
- **All questions are for research purposes only.**
- **Participation is voluntary, and you are free to withdraw from the study at any time.**
- **Your participation will be highly appreciated, thank you.**

In terms of the University's policies governing research you are requested to sign the following statement indicating your willingness to participate in this research project.

I……………………………………..……………(full names of participant) hereby confirm that I understand the contents of this document and the nature of the research project, and I consent to participating in the research project.

I understand that I am at liberty to withdraw from the project at any time, should I so desire.

SIGNATURE OF PARTICIPANT ……………………… DATE …………………

SCF Question (Please tick the appropriate box corresponding to your selection)

A. Which of the following four statements best describes your typical investment strategy?
1. Substantial financial risks expecting to earn substantial returns
2. Above-average financial risks expecting to earn above-average returns
3. Average financial risks expecting to earn average returns
4. No financial risks

1	2	3	4

13-Item Risk Tolerance Measure (Please tick the appropriate box corresponding to your selection)

A. In general, how would your best friend describe you as a risk taker?
1. A real gambler
2. Willing to take risks after completing adequate research
3. Cautious
4. A real risk avoider

1	2	3	4

B. You are on a TV game show and can choose one of the following. Which would you take?
1. R1 000 in cash
2. A 50% chance at winning R5 000
3. A 25% chance at winning R10 000
4. A 5% chance at winning R100 000

1	2	3	4

C. You have just finished saving for a "once-in-a-lifetime" vacation. Three weeks before you plan to leave, you lose your job. You would:
1. Cancel the vacation
2. Take a much more modest vacation
3. Go as scheduled, reasoning that you need the time to prepare for a job search
4. Extend your vacation, because this might be your last chance to go first-class

1	2	3	4

D. If you unexpectedly received R20 000 to invest, what would you do?
1. Deposit it into a bank account, money market account, or a short-term fixed deposit
2. Invest it in safe high quality bonds or bond unit trusts
3. Invest it in shares or share unit trusts

1	2	3

E. In terms of experience, how comfortable are you investing in shares or share unit trusts?
1. Not at all comfortable
2. Somewhat comfortable
3. Very comfortable

1	2	3

F. When you think of the word "risk" which of the following words comes to mind first?
1. Loss
2. Uncertainty
3. Opportunity
4. Thrill

1	2	3	4

G. Some experts are predicting prices of assets such as gold, jewels, collectibles, and real estate (hard assets) to increase in value; bond prices may fall, however, experts tend to agree that government bonds are relatively safe. Most of your investment assets are now in high interest government bonds. What would you do?
1. Hold the bonds
2. Sell the bonds, put half the proceeds into money market accounts, and the other half into hard assets
3. Sell the bonds and put the total proceeds into hard assets
4. Sell the bonds, put all the money into hard assets, and borrow additional money to buy more

1	2	3	4

H. Given the best and worst case returns of the four investment choices below, which would you prefer?
1. R200 gain best case; R0 gain/loss worst case
2. R800 gain best case; R200 loss worst case
3. R2 600 gain best case; R800 loss worst case
4. R4 800 gain best case; R2 400 loss worst case

1	2	3	4

I. In addition to whatever you own, you have been given R1 000. You are now asked to choose between:
1. A sure gain of R500
2. A 50% chance to gain R1 000 and a 50% chance to gain nothing

1	2

J. In addition to whatever you own, you have been given R2 000. You are now asked to choose between:
1. A sure loss of R500
2. A 50% chance to lose R1 000 and a 50% chance to lose nothing

1	2

K. Suppose a relative left you an inheritance of R100 000, stipulating in the will that you invest ALL the money in ONE of the following choices. Which one would you select?
1. A savings account or money market unit trust
2. A unit trust that owns shares and bonds
3. A portfolio of 15 ordinary shares
4. Commodities like gold, silver and oil

1	2	3	4

L. If you had to invest R20 000, which of the following investment choices would you find most appealing?
   1. 60% in low-risk investments, 30% in medium-risk investments and 10% in high risk investments
   2. 30% in low-risk investments, 40% in medium-risk investments and 30% in high risk investments
   3. 10% in low-risk investments, 40% in medium-risk investments and 50% in high risk investments

1	2	3

M. Your trusted friend and neighbour, an experienced geologist, is putting together a group of investors to fund an exploratory gold mining venture. The venture could pay back 50 to 100 times the investment if successful. If the mine is a bust, the entire investment is worthless. Your friend estimates the chance of success is only 20%. If you had the money, how much would you invest?
   1. Nothing
   2. One month's salary
   3. Three month's salary
   4. Six month's salary

1	2	3	4

Demographic Data

Age:

Gender:

Male	Female

Race:

Black	Coloured	Indian	White	Other (please specify):

Highest level of education attained:

Less than Matric	Matric	Less than 3 Year Post Matric Study	3 Year Undergraduate Degree/Diploma	Postgraduate Degree

Approximate level of annual household income (based on the latest SARS Income Tax Brackets):

< R150 000	R150 001 < R235 000	R235 001 < R325 000	R325 001 < R455 000	R455 001 < R580 000	> R580 001

Marital Status:

Single	Married	Divorced

Do you have any dependents/children (less than 21 years old)?

Yes	No

Were you raised in a household that was characterised by one of the following religions?

Christian	Hindu	Muslim	Jewish	Other (please specify):

Employment Status:

Student	Unemployed	Salaried Employment (incl. contract)	Self-employed	Retired

APPENDIX C – ETHICAL CLEARANCE

UNIVERSITY OF
KWAZULU-NATAL
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26 May 2011

Mr CK Metherell (205507115)
School of Economics and Finance
Faculty of Management Studies
Pietermaritzburg Campus

Dear Mr Metherell

PROTOCOL REFERENCE NUMBER: HSS/0261/011M
PROJECT TITLE: The Impact of Demographic Factors on Subjective Financial Risk Tolerance: A South African Study

In response to your application dated 23 May 2011, the Humanities & Social Sciences Research Ethics Committee has considered the abovementioned application and the protocol has been granted **FULL APPROVAL.**

Any alteration/s to the approved research protocol i.e. Questionnaire/Interview Schedule, Informed Consent Form, Title of the Project, Location of the Study, Research Approach and Methods must be reviewed and approved through the amendment /modification prior to its implementation. In case you have further queries, please quote the above reference number.
PLEASE NOTE: Research data should be securely stored in the school/department for a period of 5 years.

I take this opportunity of wishing you everything of the best with your study.

Yours faithfully

....

Professor Steven Collings (Chair)
HUMANITIES & SOCIAL SCIENCES RESEARCH ETHICS COMMITTEE

cc. Supervisor: Mr B Strydom
cc. Prof D Vigar-Ellis Post-Graduate Centre, School of Management