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Skewness, idiosyncratic volatility and probability weighting – how can wealth managers help clients?

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Master Thesis in Finance

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Abstract

Probability weighting, the overweighting of small probabilities and underweighting of large probabilities in a nonlinear way, describes well how most individuals form decisions under risk. Probability weighting has implications to preferences in investment, in particular the preference for assets with skewed returns.

The purpose of this thesis is to derive the extent of probability weighting, explore how probability weighting influences preferences, and explore related concepts through an experiment. We will then use the results from the experiment to discuss how to incorporate probability weighting into the wealth management process. We find that probability weighting is an important characteristic to describe people preferences; in particular, we find that about half the respondents are willing to sacrifice higher expected return and lower variance to obtain more skewed payoffs. There are large preference reversals that cannot be explained by expected utility.

Apart from the collection of data, we contribute to the behavioural finance literature with analysis of the findings and development of advices. We emphasise the use of diagnostic tools and discuss whether portfolios need products to enhance skewness.

Preface

This Master thesis is written as the final step of our Master of Science degree in finance, at the Norwegian School of Economics. This semester we have spent all our time delving into one of the most interesting topics within our specialisation in Finance. In our first year of our Master's degree we had already chosen to write about behavioural finance and wealth management. The special interest in this topic came after attending the course "Behavioural Finance and Wealth Management", given by Professor Thorsten Hens in the spring of 2015. Professor Hens gave a passionate introduction to aspects of behavioural finance, including biases, decision theory and asset allocation. The potential to apply theory in practical situations particularly appealed to us. We also found it very interesting to understand how humans behave, and the implications of this behaviour in financial markets. We gained special interest in prospect theory, especially the impact of probability weighting, and this encouraged us to further our knowledge in the field and contribute to the existing literature.

Because experimental economics is able to unlock more on how humans actually make decisions, and since the number of high-net worth individuals is rising rapidly, we are sure that this field will become increasingly important in the future. We find the combination of finance and human behaviour very interesting, and although there has been a lot of research in the field, we believe that technological improvements and the rise of behavioural finance could improve the understanding of the human brain, and make this field evolve even further. This thesis will contribute to this evolution by providing new data on preferences among individuals and the extent of probability weighting. We sincerely hope our Master's thesis will provide valuable information to the private banking sector on how to incorporate probability weighting in wealth management processes.

Acknowledgements

We are grateful for the help and guidance our supervisor, Professor Francisco Santos, has provided. He has challenged our ideas and given us helpful advice through the entire process. We particularly value his honesty and how he explains complex concepts in an easily understandable manner. We are grateful for all the help and guidance. We would also like to thank Thorsten Hens, who has given us essential information and different perspectives on the theory.

1 Introduction

Why are people paying to take certain risks with a negative expected value, while at the same time paying a premium to avoid other risks? Why are people buying lottery tickets while still holding insurance?

A risk-reward framework fails to reconcile this. Could it be that people prefer certain payoff structures, and avoid others, or are people interpreting probabilities in a non-objective manner?

The market for lottery tickets might be trivial and of little importance to the financial markets that keeps the wheels turning in the world economy. What if the same kind of risk taking also resembles human decision-making in financial markets that we are critically depend upon? Does this inconsistency in risk taking influence how the markets operate, or is it only background noise?

Experimental studies have shown that human behaviour might deviate considerably from what decision theory dictates as rational. Are results from experimental studies only saying something about how people will behave in experimental settings, or could these theories be applied to the trading floors and help explain how money managers invest your grandmother's pension? Behavioural finance is a field within finance that has the ambition of being applicable.

Behavioural finance is built on experimental results from laboratories on how people really behave, this is used to explain behavioural patterns in financial markets. Understanding human decision-making is difficult. Often, there is only one way to be rational, but there are an unlimited number of ways to be irrational. However, if people are irrational in a predictive way, behavioural finance can provide you with a powerful framework to understand why, and what the next move might be.

In wealth management, understanding the market is necessary but not sufficient. The tools of mean-variance analysis, asset pricing and efficient market hypothesis are helpful in understanding how financial markets are operating. Wealth managers also have to understand their clients to provide financial advice. Here, behavioural finance is a state-of-the-art tool to address these issues. The advisory process of affluent individuals is particularly well-suited for the application of behavioural finance, as these processes are mostly tailor-made for the clients.

In this thesis, we look at how people treat probabilities. Prospect theory, a theory derived from experimental research, predicts that people make choices as if small probabilities were larger and large probabilities were smaller. In this thesis, we will explore the extent of this manner of treating probabilities in decision-making under risk, while we aim to provide wealth managers with guidance on how to advise clients.

1.1 Thesis Purpose

This thesis aims to address how investors are affected by probability weighting in the investment process, and to highlight how wealth managers could give tailored advice to clients who experience probability weighting. We hope to provide some new insight on the topic, which could possibly lead wealth managers to consider probability weighting when giving financial advice.

1.2 Structure of the Paper

Our thesis is structured in the following manner: In section 2, we present the relevant theory to better understand the work conducted in this thesis. We describe the development of prospect theory. We briefly explain the value function and probability weighting from prospect theory. We also contrast prospect theory with other theories of decision under risk.

In section 3, we do a literature review to motivate the purpose of our survey and data collection. There is a clear link between the literature presented and the data collection.

Section 4 is dedicated to the methodology of the survey. Discussing the survey objective, the survey design, participants, and participants' incentives for participating in the survey.

In section 5, we present the findings from our survey, and propose plausible explanations to these findings.

In section 6, we employ the empirical findings of the survey and discuss the findings in light of theory and literature, in order to provide wealth managers with recommendations on how to incorporate probability weighting into the wealth management process.

In section 7, we draw conclusions and address further interesting research areas.

2 Theoretical Background

This section first presents decision theory, which include expected utility, mean-variance analysis, and prospect theory. We present all theories to provide a general understanding of decision under risk. However, the majority of this section will be dedicated to prospect theory and probability weighting, which is the main topic for this master thesis. The description of prospect theory will highlight key elements of the theory, namely 2.2.1 The Value Function, 2.2.2 The Loss and Risk Aversion, and 2.2.3 The Probability Weighting. Then, the purpose is to explain biases related to probability weighting. This includes 2.2.4 Overconfidence. The purpose of the theory section is to explain how probability weighting theoretically affect people and which biases this could lead to. This part builds the theoretical foundation for this thesis and is important for the further understanding of the thesis.

2.1 Decision Theory

The history of decision theory goes back to the 17th century, but it is still an active research area. Decision theory is based on choice under uncertainty. There exists two approaches to decision theory: the prescriptive approach and the descriptive approach. The prescriptive approach describes how people should make a decision, and assumes that the decision maker is fully informed and rational. Contrarily, the descriptive approach describes how people actually make decisions. The prescriptive approach includes the psychological condition and does not assume that the investor is always acting rationally.

2.1.1 Expected Utility Theory

Expected utility theory is a prescriptive theory about decision-making under risk. Decision-making under risk can viewed as a choice between prospects or gambles with different levels of risks. When an expected-utility investor is taking a decision under risk, the investor thinks in terms of final wealth, and choose the outcome that gives the highest expected value. The most preferred outcome for the expected-utility person does not only depend on the highest expected wealth for the particular investor, but also depends on the person’s risk aversion. A person is risk averse if the person will not accept a fair gamble. In the theory of expected utility, risk aversion is equal to the concavity of the expected utility function.

In 1944, Von Neumann and Morgenstern introduced the axioms of rationality, which postulates the requirements for a decision to be rational. Von Neumann and Morgenstern proved that expected utility was the only theory that was consistent with axioms. The axioms for rational choices are monotonicity, transitivity, and independent axiom. The axiom of monotonicity is satisfactory if the investor prefers the lottery with the highest payoff when comparing two lotteries. The axiom of transitivity is satisfactory if the investor prefers stock to bonds and bonds to commodity then the investor must also prefer stock to commodities. The independence axiom is satisfactory if the investor is confronted with two different lotteries, and then a mixture of each lottery with a third lottery, then the preference of the two lotteries should be independent of the third lottery used. If the investor satisfies the axiom of rationality, the investor's decision-making under risk is rational according to expected utility theory.

2.1.2 Mean-Variance Analysis

Harry Markowitz introduced Mean-Variance Analysis in 1952. Mean-Variance Analysis is a prescriptive theory, and proves the link between risk and return. According to Markowitz' theory, the investor should maximise expected return and minimise the variance. The investor should choose the efficient portfolio, which is the portfolio which maximises the return, given a level of risk. The risk level depends on the investor's risk aversion. A higher risk aversion leads to a portfolio with a lower level of risk. The two-fund separation theorem introduced by James Tobin demonstrates that mean-variance investors hold the same composition of assets, but optimise their risk preference by their weight in the market and the risk-free asset.

2.2 Prospect Theory

Kahneman and Tversky introduced prospect theory in 1979. The theory originates from economic experiments and is able to describe human behaviour in an experimental setting as well. The theory is based on how people form decisions under uncertainty. Their article was the breakthrough for behavioural finance, introducing an alternative model to the perceived undescriptive decision making model of expected utility. Today, their paper is one of the most cited articles, and Kahneman was the first non-economist to receive the Nobel Memorial Prize in Economic Sciences in 2002.

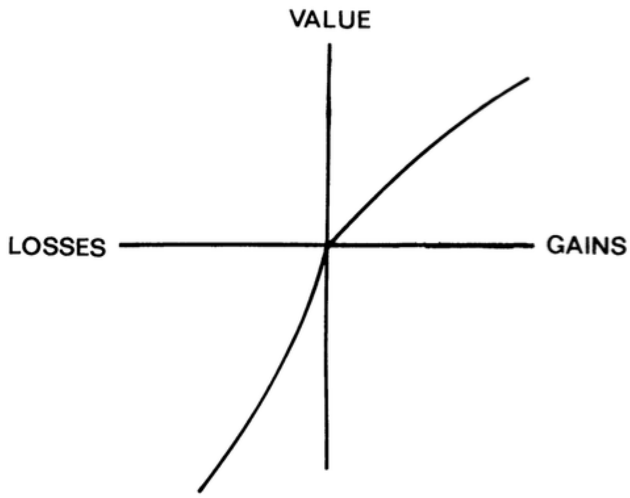
Prospect theory is a model based on several key elements included in the two phases of the choice process. First, there is the editing phase, where the decision maker parses different prospects. Then, there is the evaluation phase, where the investor considers and selects the prospect with the highest value.

2.2.1 The Value Function

The value function displays the preference of a prospect investor. It indicates how a prospect investor prefers gains and losses to a relative reference point. Here, the reference point usually relate to an initial value, like the purchase price of the asset, or the risk-free rate or a benchmark multiplied with the wealth. The changes in wealth according to the reference constitute a crucial aspect of the prospect theory, as it looks at the evolution of the investment, in contrast to other theories where the emphasis is on the final state. (Kahneman and Tversky, 1979)

Since the theory identifies that prospect investors react differently when facing gains than losses, the value function is S-shaped with a concave form for gains and convex form for losses (figure 1). The investor becomes risk-averse when there is a high probability for gains and risk-seeking if there is a high probability for losses. This indicates that for both gains and losses, normally the marginal value decreases with the scope. (Kahneman and Tversky, 1979)

Figure 2.2.1-1 – A hypothetical value function



Source: (Kahneman and Tversky, 1979)

This figure displays the value function. The function is concave for gains and convex for losses to indicate that it hurts more to lose than to gain. At the reference point, the function is the steepest. According to Kahneman and Tversky (1979), responses to gains and losses in a riskless connection has given the shape of the value function.

In the next section, risk aversion and loss aversion are explained further.

2.2.2 Risk Aversion and Loss Aversion

Risk aversion and loss aversion play a crucial part in prospect theory. Risk aversion relates to the investor's view on volatility in the returns of an asset. According to Kahneman and Tversky (1979), *a person is risk averse if he prefers the certain prospect (x) to any risky asset with expected value x.*

Risk aversion in prospect theory differs from expected utility, because in the area of gains, the investor is risk-averse, while in the area of losses, the investor is risk-seeking (except from small probabilities). This indicates that risk aversion is asymmetric. (Kahneman an Tversky, 1979)

Loss aversion defines how investors react to losses. The median prospect investor will dislike losses around two times as much as he or she values gains. However, the behavioural parameters may depend on cultural differences. This explains the more aggressive slope of the value function for losses compared to gains. Hence, a high loss aversion means that the investor will require a high premium. (Hens and Bachmann, 2011)

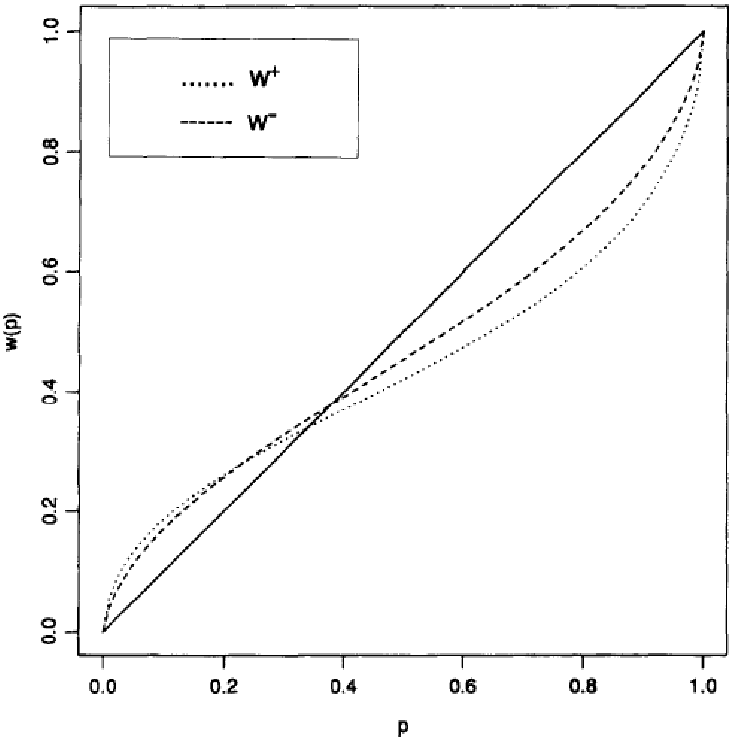
The average value founded for risk aversion is α=0.88 and for loss aversion β=2.25. (Tversky and Kahneman, 1992)

2.2.3 The Weighting Function

The weighting functions describe how people deal with probabilities. It is based on the fact that people tend to overvalue small probabilities and underweight more likely events. People do not treat objective probabilities linearly. This can explain why some people buy both lottery tickets and insurance. People overvalue probabilities even if they know the true probability.

For a prospect-theory person there is a huge psychological step from an impossible event to an event with a probability of 0.001 percent. The event is then evaluated as possible. Hence, in contrast to expected utility, prospect theory uses decision weights instead of probabilities to consider this psychological aspect. The weighting function highlights investors' irrationality towards probabilities and measures the desirable outcome of the prospect. The weighting functions are inverse S-shapes and show the perceived probabilities instead of the actually probability of an event to occur. (Tversky and Kahneman, 1992)

Figure 2.2.3 – Weighting function for gains (w+) and for losses (w-)



Source: (Tversky and Kahneman, 1992)

Figure 2 presents how people handle probabilities. In the area of 0.0 to 0.4, the probabilities are overweight, while in the area of 0.4 to 1 the probabilities are underweight. In addition, the figure presents the difference between positive outcomes and negative outcomes.

A. Such values can be calculated by employing the following formula:

$W^{+}(p) = \frac{p^{\gamma}}{(p^{\gamma}+(1-p)^{\gamma})^{\frac{1}{\gamma}}}$ $W^{-}(p) = \frac{p^{\delta}}{(p^{\delta}+(1-p)^{\delta})^{\frac{1}{\delta}}}$

Gamma values are distributed between 0 and 1, depending on the severity of the individuals' probability weighting. γ=1 entails no weighting for gains, and γ=0 entails infinite probability weighting. Similarly, the delta values are distributed for probability weighting in the domain of losses. Tversky and Kahneman (1992) finds in a field experiment that the median value of probability weighting under gains are γ=0.61 and δ=0.69 for losses.

In addition, Tversky and Kahneman (1992) introduced the fourfold pattern of risk attitude, which displays an empirical general view about choices under risk (Table 1). Table 1 presents how people act differently according to their probabilities of gains or losses. When probabilities for gains are high, people value a certain amount rather than the risk taking. While with a small probability of gain, people value the gamble higher than the expected amount. For losses, this is opposite. For small-probability losses, people prefer certain loss rather than a lottery with same expected value but with the possibility of breaking even. For high-probability losses, people are willing to take risk to incur a certain loss. This explains why people play the lottery even if the probability of winning is small. (Tversky and Kahneman, 1992)

Table 2.2.3 – The fourfold pattern of risk-taking behaviour

	Losses	Gains
Small probability	No risk-taking	Risk-taking
Moderate to high probability	Risk-taking	No risk-taking

In 1992, Tversky and Kahneman published a sequel to the 1979 article, presenting a more numerical approach to prospect theory, addressing the cumulative prospect theory, using a normalized prospect theory utility, which applies probability weighting to the cumulative distribution function instead of the probabilities. In the first article, the probabilities were a monotonic transformation into weights. This led to two problems. First, the assumption of stochastic dominance was not constantly contended, which is important for the theorists to satisfy. Another problem was to handle chances with a large number of outcomes. The revised model transforms the entire cumulative distribution function instead of each probability, thus overcoming this problem. (Tversky and Kahneman, 1992)

The weighting function is an important part of prospect theory, and this is the main part that distinguishes prospect theory from expected utility theory. Probability weighting leads to violation of the axiom “more wealth is better than less wealth”. Therefore, probability weighting makes the theory irrational. People seem to value possibilities more than probabilities.

2.2.4 Overconfidence

Overconfidence is a tendency to evaluate own precision in estimates to surpass the actual accuracy. In certain experiments, people have been asked to provide a 95 confidence interval of the population of distant countries. People tend to have very narrow confidence intervals on such predictions even though they have little knowledge of the true number. This indicates overconfidence. Overconfidence could lead to excessive trading, because the investors are confident about the trading and think they can beat the market. Overconfidence is thus a behavioural bias.

3 Literature Review

The purpose of this section is to do a short literature review on the behavioural finance literature concerning probability weighting and related concepts important to our thesis. Idiosyncratic volatility puzzle, why stocks with large price fluctuations tend to earn lower return, is reviewed in section 3.1.1. In section 3.1.2, we review the idiosyncratic skewness puzzle, why stocks with potential for extreme positive gains tend to be overpriced. We also include literature review of the under diversification among investors, and how this could be linked to probability weighting, in the review of the trade-off between skewness and mean variance efficiency in section 3.1.3. In section 3.1.4, we also review some literature on sensation seeking, and overconfidence, with behavioural explanation of high trading frequency. In section 3.1.5, we briefly review a study on cultural differences regarding behavioural parameters important for investments decisions.

The literature reviewed is relatively novel. By employing behavioural explanations, the literature in question has been successful in providing plausible explanations to the phenomena in financial markets. The ability to provide explanations and its applicability have fuelled interest in this research among financial economists. Interest in applying results from experiments in behavioural finance on real financial markets have gained momentum.

3.1 Probability Weighting and Asset Preference

Probability weighting can influence the attractiveness of a security, which financial theories based on mean variance fail to address. Barberis and Huang (2008) discuss the implications of probability weighting on security pricing. Barberis and Huang (2008) argues that the asymmetry of the asset return distribution can be priced. Probability-weighting investors would put more emphasis on extreme outcomes that happen rarely and less on the most frequent outcomes. Positively skewed stocks (stocks with a long right tail in the return distribution) would thus be highly demanded in this model because the right tail is over weighted. High demand for such stocks reduces the long-term expected return of such assets. Barberis and Huang (2008) argue that this could be a potential explanation for some of the puzzles in finance, such as the low long-term return of IPOs, low diversification among household equity portfolios, and the overpricing of out-of-the-money options. Such concepts are puzzling in the mean-variance perspective, but less puzzling seen in the light of cumulative prospect theory.

Bjørn Eraker and Marek Ready (2015) test the Barberis and Huang (2008) model on OTC stocks in the USA. OTC stocks are stocks that are less regulated than listed stocks. OTC stocks have less liquidity than listed stocks. Lower liquidity should increase the rate of return to compensate for the high cost of trading these assets. Eraker and Ready (2015) find extremely poor returns on the stocks trading OTC, yielding -32% on average in yearly returns. The return distribution of these stocks are positively skewed. Eraker and Ready (2015) find that to reconcile the results, investors trading in OTC stocks must have behavioural parameters for probability weighting close to the median parameters of Kahneman and Tversky. This pattern is yielding supporting evidence for the Barberis and Huang (2008) model.

Campbell et al. (2008) investigate the stock market for financially distressed companies. They find that distress stocks earn poor returns, have higher beta, higher standard deviation and other risk loadings than the market. Campbell et al. (2008) find such stocks yield skewness regardless if held in concentration or held in diversified portfolios, appealing to the type of investor with strong probability weighting.

The model of Barberis and Huang (2008) suggests that the puzzles of idiosyncratic volatility and idiosyncratic skewness might be interlinked, and probability weighting explains these puzzles.

3.1.1 The Idiosyncratic Volatility Puzzle

Diversification easily and efficiently eliminates idiosyncratic volatility. Because diversification eliminate this type of risk, investors should not be compensated for holding this type of risk, and asset returns should not reflect this risk. Ang et al. (2006), finds a puzzling result of high idiosyncratic volatility is accompanied by significantly low returns, contrary to intuition. Ang et al. (2006) argue the opposite of Merton (1987), who suggests that stocks in certain situations could earn some premium due to high idiosyncratic volatility, because of information segmentation. Ang et al. (2006) find that there is a 1.06% monthly return difference between the lowest quintile of idiosyncratic volatility and the highest quintile of idiosyncratic volatility. Ang et al. (2009) find a similar pattern, but the difference in return between high and low idiosyncratic volatility stocks is amplified when also evaluating international markets, and by evaluating a larger sample of U.S. data.

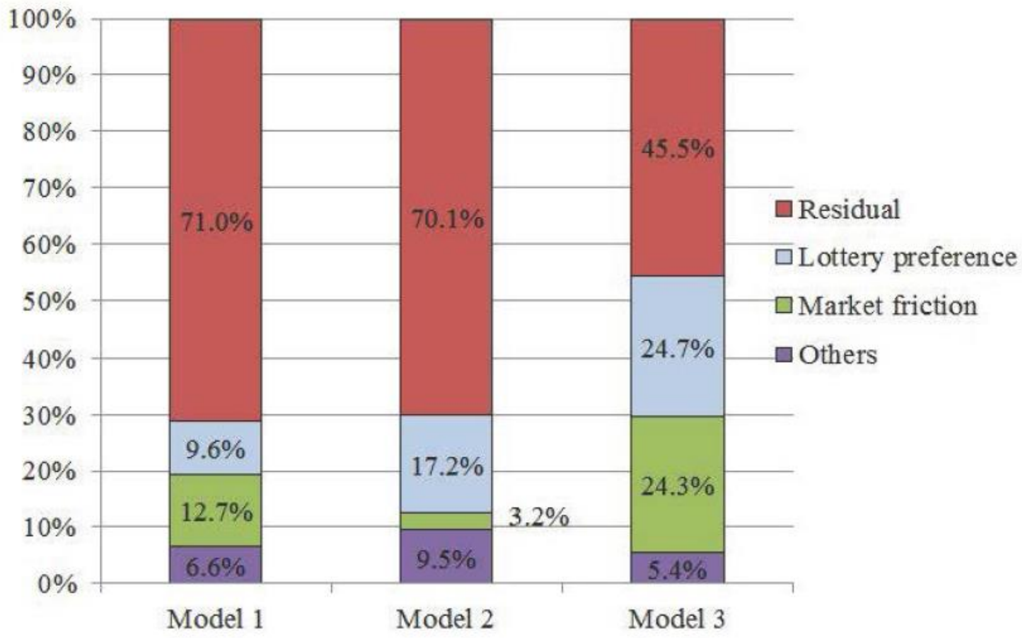
Ang et al. (2006) do not provide any single explanation for what causes this puzzle, but rather suggest a number of potential explanations, including skewness-preferring investors. The idiosyncratic skewness literature that we are reviewing in the next section provide explanations for the results. The skewness literature argue that big positive shocks, although they happen very infrequent, are viewed very positively among investors if there is asymmetry in the shocks. Idiosyncratic volatility could thus be linked to high positive skewness. Furthermore, investors might not be able to assess the positive skewed stocks, but only partially detect the highly skewed stocks by observing different factors that they interpret as signs of high skewness. In light of this, high idiosyncratic volatility can be seen as a signal for skewness-preferring investors in search of positively skewed stocks. This argument is parallel to the argument of Boyer, Mitton and Vorkink (2009), who argue that investors take volatility as proxy for evaluating skewness.

It is important to see that skewness changes over time, such that what matters for investors is not skewness itself, but their perception of skewness in assets. Investors might seek skewness without obtaining it. Because of this, there are different models to find the best skewness prediction. Siddique and Harvey (2000) use a simple model of past skewness to explain future skewness. However, such a model has limited ability to detect skewed return distributions.

There are also alternative explanations to the volatility puzzle. A broad category of these explanations focuses on market frictions or methodology issues of the Ang et al. (2006) article. Fu (2009) and Huang et al. (2010) question the methodology. While Han and Lesmond (2011) explain the puzzle on the basis of market friction in the Ang et al. (2006) article. Firstly, the effect of the bid-ask bounces drive volatility estimates to be biased. Second is the use of zero returns, which have consistently low volatility because of no trading. Lesmond and Han (2011) use bid-ask midpoints and find that in using this approach, the effect of idiosyncratic volatility on driving returns diminishes to zero.

In the article by Hou and Loh (2012), they solved the idiosyncratic volatility puzzle by testing different models to assess which explanation best explained the volatility puzzle. Although, most of the explanation is residual, and thus not explained within the model. Among the explanations within the model, it seems as if the lottery preferences perhaps is the most successful in explaining the idiosyncratic volatility puzzle.

Figure 3.1.1 – Hou and Loh (2012) Explanations to idiosyncratic volatility puzzle



3.1.2 The Idiosyncratic Skewness Puzzle

Boyer, Mitton and Vorkink (2009) was motivated by the Ang et al. article and the idiosyncratic volatility puzzle. Boyer, Mitton and Vorkink (2009) wanted to test if idiosyncratic volatility was only a prediction of skewness, and thus worked to attract investors to high-volatility stock who were actually in search of high-skewness stocks. Boyer, Mitton and Vorkink (2009) provide three arguments to explain how higher idiosyncratic volatility can explain higher idiosyncratic skewness. These arguments are of crucial importance in understanding why these two concepts are interlinked.

Firstly, volatility amplifies skewness. Stock companies are limited liability companies, such that very volatile stocks are positively skewed by construction. The limited liability of stock companies ensures that there is a limited downside and the high volatility ensure a high upside potential.

Secondly, there is a large amount of literature linking a company's growth options to idiosyncratic volatility (Cao et al. (2006), Barinov (2011)). Growth options should thus positively impact both volatility and return.

Thirdly, volatility could be correlated with companies in technological revolutions, during which there might be shakeouts, such that some firms earn market power while others perish.

During the shakeout period, there is high idiosyncratic volatility reflecting the uncertainty of which companies will sustain in the industry. After the shakeout, the firms that survived the industry shakeout have substantial upside potential because the shakeout could create firm market power. The surviving companies of a technological revolution thus have skewed return distributions because of the market power.

Boyer Mitton and Vorkink (2009) see idiosyncratic volatility as one of several components in the expected skewness model. Other variables also help explain skewness, such as turnover and momentum. Momentum is negatively correlated with expected skewness. Momentum stocks have more negatively skewed return distributions. Turnover is seen as a proxy of investors' disagreement, and in periods of high turnover, skewness is expected to be negative.

Applying the three variables to American stocks over more than a 30-year timeline, Boyer, Mitton and Vorkink (2009) form a portfolio that rank stocks by their expected skewness, based on the momentum, turnover and idiosyncratic volatility of the previous month. Boyer, Mitton and Vorkink (2009) find that significant differences in the return on stocks ranked on expected idiosyncratic skewness. This contradicts Markowitz(1952) who postulates that idiosyncratic risk does not affect the rate of return. Idiosyncratic skewness matters both statistically and economically. Furthermore, the realized return diminishes monotonically in the five quintiles of stocks ranked by skewness, indicating that there is some stable negative relationship between skewness and returns.

The most skewed quintile of stocks has a Fama–French-adjusted alpha of -0.86% per month, while the lowest skewness quintile have a Fama–French-adjusted alpha of +0.14%. A long high low expected skewness short high expected skewness has a Fama–French-adjusted alpha of 1.00% per month. Boyer, Mitton and Vorkink (2009) suggest the following dynamic to explain their result. Some agents in the market have preference for skewness, and those hold few stocks and overbuy the highly skewed stock, driving down long-term returns for such stocks. Although there could be multiple explanations for this result, preferences for lottery payoffs derived from probability weighting seem to be a highly plausible explanation for the results.

3.1.3 The Trade-Off Between Skewness and Diversification

Mitton and Vorkink (2007) evaluated a dataset of 60,000 client accounts. Mitton and Vorkink (2007) argue that there are heterogonous preferences for skewness among investors. Some investors sacrifice the mean-variance efficiency of diversification in order to maximize idiosyncratic skewness in their portfolio.

Idiosyncratic skewness-preferring investors want to maximise the possibility of an extremely positive payoff. To maximise such a chance diversification is not attractive. Some investors tend to prefer positively skewed stocks, and although diversification eliminates undesired variance, diversification also eliminates desired skewness. By choosing stocks with high positive skewness, the investors are able to maximise the upside potential. Looking at the top 1% of investors based on return in the period, Mitton and Vorkink (2007) finds that undiversified investors outnumber diversified investors by 26 to 1.

The average number of stocks is much smaller than what should be expected from theory of portfolio allocation. Meir Statman (2009) argues that in order to obtain complete benefit from diversification, at least 30 stocks have to be held by the investor. In the client data, the average number of stocks held by individuals is only 4.

The least diversified investors hold stocks with an idiosyncratic skewness coefficient that is almost twice as large as the average individual stock selected by diversified investors. This pattern indicates that investors that are under-diversified have consciously chosen highly positively skewed stocks. Because skewed stocks also tend to have higher variance, the under-diversified investors tend to have extreme amounts of risk in their portfolio.

Gutzemann and Kumar (2008) studies the same client accounts as Boyer, Mitton and Vorkink (2009). Gutzemann and Kumar (2008) find that diversification increase in age, education, wealth, and income. Gutzemann and Kumar (2008) also find that more sophisticated investors, those who trade options, do short sales, and have longer investment experience, tend to hold more diversified portfolios. In addition, people who hold international stocks tend to diversify also with domestic stocks. Gutzemann and Kumar (2008) suggest skewness preference as one out of several explanations to under-diversification. The investors who hold stocks with the highest idiosyncratic skewness and idiosyncratic volatility are the least diversified. Gutzemann and Kumar (2008) reject the explanation that portfolio size or transaction costs explain the under-diversification. Only for a very small group of investors can superior information explain under-diversification.

It is hard to explain the tendency to under diversify when diversification is cheaply and efficiently obtainable, unless one considers the preferences which are explained by probability weighting.

3.1.4 Sensation Seeking, Overconfidence and Trading Losses

There are evidence suggesting that individuals have poor ability to appropriate the gains from holding stocks. Barber et al. (2008), finds that investors have significant losses from excessive trading. The losses of private investors from trading are staggering 3.8% of their portfolio aggregate. That is by changing to a simple buy-and-hold strategy instead of trading Taiwanese investors, which could have improved their rate of return on average by 3.8% of the invested amount annually.

Barber et al. (2008) find that the average trading volume among the Taiwanese is around 3 times that of the Americans. Barber et al. (2008) suggest that sensation seeking among investors could be an explanation for the behaviour of the Taiwanese investors. For sensation seekers, stocks with lottery-like payoffs are very appealing, while low-volatility and low-skewness stocks are boring.

Odean (1999) uses the same client accounts as the Mitton and Vorkink (2007) paper and finds similar relationships for U.S. individual investors. U.S. individual investors trade against more informed institutional investors, but trade less frequently. Losses from excessive trading is in the range of 2% of the portfolio aggregate annually for the American individuals in the survey, suggesting American individuals could also improve considerably by changing to a buy-and-hold strategy.

In the article by Grinblatt (2009), the authors find a pattern of overconfidence and sensation seeking among individuals driving some of the investors' demand for stocks. The author wants to test if non-financial sensation seeking correlates with sensation seeking in stock trading. The author matches speeding tickets with trading information to see if people who have more speeding tickets will have a higher turnover in stocks. They also match record from the finish army contain psychological information on peoples self-confidence to determine if investors' overconfidence drives turnover. They find a significant relationship between sensation seeking and overconfidence in trading. However, sensation seeking and overconfidence differ as sensation seeking makes the investor want to hold new stocks, driving trading volume, while overconfidence makes the investor assign too small confidence intervals to their probability estimates. However, both could explain gambling-like behaviour, which contrasts the prudence and patience required to gain from investment. Probability-weighting investors with a preference for lottery payoffs will probably lose more if they are sensation seeking and overconfident.

3.1.5 Cultural Differences

The intra study by Rieger et al. (2011) documents that probability weighting holds as a robust relationship internationally. Prospect theory works particularly well at describing behavioural aspects of investment behaviour. There are large cultural differences when it comes to probability weighting. The difference between countries can be enormous. Consider the median Lebanese, who has a median gamma value of 0.25, while the average Argentinian has a gamma value of 0.70, according to the intra study. An objective probability of 1% will be treated as if the actual probability was 10.62% by the Lebanese, and the Argentinian would treat the same objective probability of 1% as if the probability was 3.8%. Rieger et al. (2011) find that a large degree of these results can be explained by culture, while other factors such as macroeconomics fail to explain such differences.

4 Methodology

Motivated by the advances of behavioural finance literature, the next section will explain a survey which was conducted to explore the preferences related to probability weighting, the accuracy of subjective estimates to key investment probabilities, overconfidence, as well as gathering information on personal characteristics and investor experience. The objective of the survey is to use the results to provide concrete financial advice to different respondents of the survey.

4.1 Survey Objective

To ensure objective data collection, it is crucial to determine the survey objectives' ex ante. The survey should be designed such that the distributed questions are set to meet the objectives of the survey. This stands in contrast to looking for random trends in a set of questions distributed.

The objectives of this survey were to explore probability weighting, which include preference for skewness, probability estimation, overconfidence and investor experience. It was vital to collect data on this, to test different prediction from theory, as prospect theory, expected utility and mean-variance theory have conflicting prediction of preference in the questions at hand, as discussed in the survey design.

As we will discuss the use of the diagnostic tools in the advice part, it was important to determine if the type of questions distributed in this survey could be used in diagnostic tools in the wealth management process. Would the questions from the survey be suitable in determining behavioural parameters in a wealth management process?

In particular, the objective of the survey was to give answer to the following questions:

- For small probability events does the willingness to gamble depend on the event being a gamble with potential to gain or a loss with potential to break even?
- To what extent are people willing to trade skewness for mean-variance efficiency?
- Could biased probability estimation explain the willingness to hold equity investments?
- Are respondents who think they are able to outperform the market overconfident?

4.2 Survey Design

The survey was designed in Qualtrics, which is a free, online software solution for designing surveys. Designing the survey online was preferable for several reasons. Distributing the survey was convenient when the survey was already made online. Designing the survey in Qualtrics made it possible to use display logic, such that questions would appear based on previous answers given by the respondents. Furthermore, there were also advantages to analysing the results when the survey was designed in Qualtrics.

One of the objectives was to test how people treat small probabilities, to see whether this could best be explained by expected utility or by prospect theory. Expected utility predicts respondents to have the same risk aversion for gains and losses, while prospect theory predicts risk seeking in small-probability, large-gain payoffs with risk aversion for large losses with small probability. To test this, we designed four questions. In the first question, the respondent could choose between a safe payoff of 4,000 NOK, and a risky gamble with a 1% probability of gaining 200,000 NOK and a 99% probability of gaining 0 (zero) NOK.

The second question was designed to capture the exact weighting of the same gamble as the first question, by letting the individual assign a value “x”, which was equal to the smallest probability of obtaining the gain, and “1-x” of obtaining 0 that the person would prefer the gamble to the safe outcome.

The third question was symmetrical to the first question, but was designed to see if the person would prefer a certain loss to a gamble with a small probability of large loss and a large probability for breaking even. Respondents were asked to choose between a certain loss of 4,000 NOK, or a risky gamble with a 1% probability of losing 200,000 NOK and a 99% chance of breaking even.

The forth question was symmetrical to the second question, and asked the respondents to assign the highest probability of “x” to prefer the gamble over the safe outcome. “X” would be equal to the probability of the loss of 200,000 NOK and 1-x equal to the payoff of zero.

Barberis and Huang (2008) have a clear prediction that people prefer skewed payoffs and are willing to accept lower returns and higher variance to obtain such payoffs. Therefore, it was interesting to test whether this preference would make people trade mean-variance efficiency for skewed payoffs. To test this, we formulated a question where the respondents were asked which lottery they preferred: Lottery A, with a 40% chance of winning 4,000 NOK and a 60% chance of winning 5,000 NOK; or lottery B, with a 98% chance of winning 4,200 NOK and a 2% chance of winning 10,000 NOK. Lottery A has higher mean and lower variance, but is negatively skewed, while lottery B has a very high skewness. It would also be important to know if lottery components should be included in the portfolio based on the preference for skewness.

We also wanted to obtain data on the respondents' ability to estimate probabilities which are key for investment decisions, and to obtain the data required to see if products such as barrier protection or portfolio insurance could be advised. The respondents were asked to estimate the probability of the OBX index on Oslo Stock exchange losing 20% sometime within a year, lose 40% sometime within a year. We also asked the respondents to estimate the probability of a loss of 20% in exactly one year, 40 in exactly one year. Respondents were given information about the OBX index.

It was also an objective to obtain data on how the perceived relative importance of investment strategy, product selection and market timing. This to know whether a certain deviation could be used in the wealth management process.

We also wanted to learn more about related aspects, which would be important to determine for wealth managers who are interested in how people treat probabilities, such as overconfidence. To obtain information on this, we asked respondents to provide a confidence interval on the population of Switzerland, which with a 90% probability included the actual probability. Similarly, for the population of Papua New Guinea, we asked for a confidence interval which with 90% certainty included the actual population. Here, we were interested in knowing if people assigned a wide enough estimation of the confidence interval to account for the uncertainty of their estimates.

We also wanted to obtain information on investment experience to learn how this correlates with the responses in the survey. We asked respondents to provide information on the asset classes they had invested in in the past 12 months. The next questions were conditional, and if respondents had not invested the past 12 months , the questions were not asked.

Conditional on the respondents having experience in trading stocks, the respondents were asked about the number of stocks held in the portfolio.

Conditional on the investors having invested in stocks or derivatives the past 12 months, the respondents were asked if the investment strategy outperformed a buy-and-hold strategy, either of holding a diversified fund or holding the index.

Conditional on the investors having invested in stocks or derivatives the past 12 months, the respondents were asked to briefly describe the investment strategy. This qualitative information could be used to understand whether the respondents conducted arbitrage-pricing investments.

Conditional on the investors having invested in structured products in the past 12 months, the respondents were asked whether the wealth manager used a diagnostic tool.

We also obtained information on the respondents' gender, age, educational background and country of birth.

The actual design of the survey is included in the appendix.

4.3 Participants

The choice of methodology is controversial from a research point of view. This raises several concerns. In the survey, mainly bachelor and master degree students in economics, strategy, finance or business were participants. Intentionally, the population was unrepresentative. Although this is controversial, there are several strong arguments for this approach.

The survey questions require quantitative understanding and reasoning. Some familiarity with indexes and understanding of concepts such as market timing, product selection, and investment strategy was crucial to receive competent responses. In addition, the questions regarding lotteries require an understanding of decision under risk. With the lottery questions, we study probability weighting as a preference, and not probability misestimating, and to ensure this, numerical estimation is required. Students in these specializations are assumed to have a strong ability to provide accurate responses to such questions.

4.4 Incentives

There might also be concerns related to the incentives of the students participating in the survey. The questions were hypothetical in nature, and thus there was no payment contingent on the responses provided. The participants did not have any monetary consequence on providing the right answer. As this is a Master’s thesis, the respondent were not given any payments contingent on the answer provided, neither have proper incentives to compensate for the time participants spent on the survey. To encourage people to participate in the survey, a prize valued at 600 NOK was drawn at random among the participants.

5 Empirical Findings

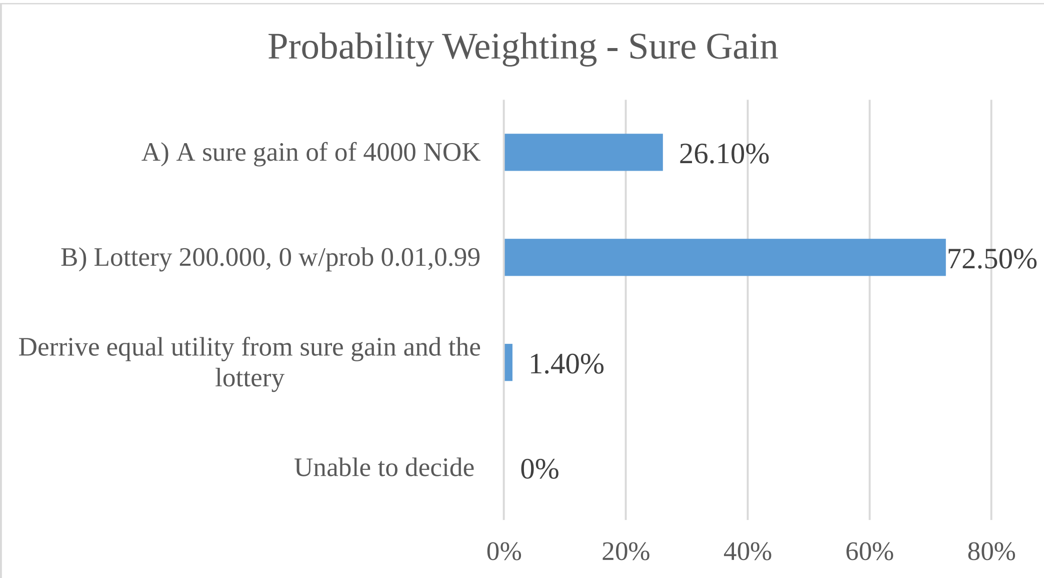
In this section, the results from the survey will be presented.

5.1 Probability Weighting for Gains and Losses

A key determination of probability weighting is to explore if respondents are risk-averse or risk-seeking in regards to large-impact outcomes with small probability. Prospect theory predicts risk taking in small-probability events with potential to gain, and risk aversion in small-probability large outcomes with possibility of losing. The lotteries were set such that the safe amount exceeded the expected value of the lottery when there was potential for gain. Similarly, the lotteries were set such that the expected loss from taking the lottery was smaller than the certain loss. Prospect theory predicts that people with probability weighting will prefer the lottery in question 1 and the certain loss in question 3, while expected utility predicts the certain gain in question 1 and the gamble in question 2.

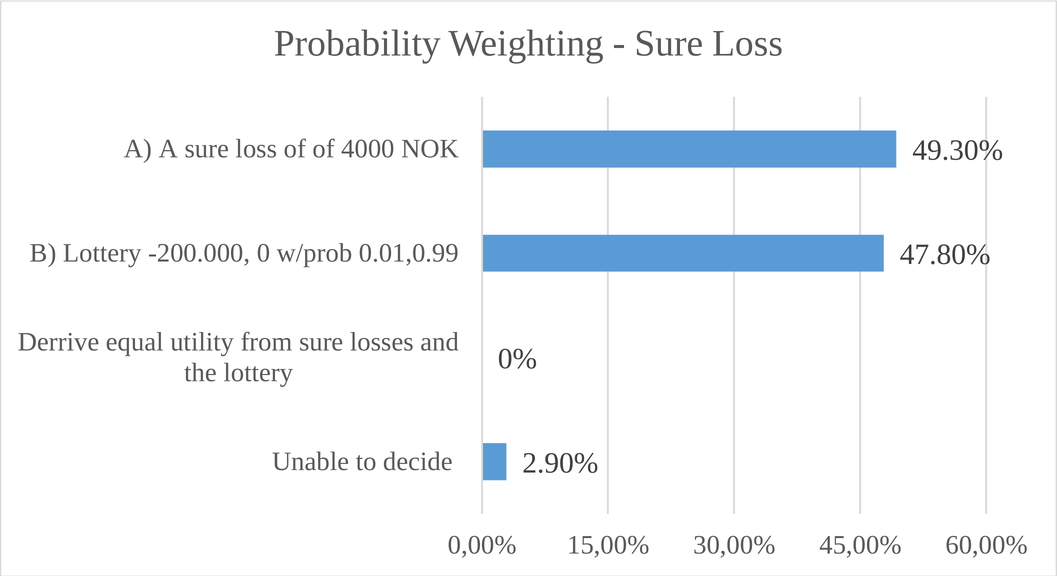
In the table below, we see that the clear majority of 72.50% has chosen the lottery over the certain outcome. From the probability weighting function for gains in section 2.3, the implied gamma value of accepting the lottery is lower than $\gamma = 0.8470$. 72.50% of the respondents have a probability weighting to this degree. 26.10% prefer the safe outcome and hence have preferences that can best be captured by expected utility.

Figure 5.1.1 – Probability weighting –sure gain



In the table below, we see that the risk attitude changed when the lottery could avoid a loss with certainty. 49.30% prefer the safe outcome to the gamble.

Figure 5.1.2 – Probability weighting- sure losses



Question 1 and question 3 should be seen as interconnected, and it is thus more interesting to see the actual change in risk seeking.

Table 5.1.3 – Preference reversal

	A→A	A→B	B→A	B→B
Number of respondents	12.12 %	15.15 %	39.39 %	33.33 %

From the table over one can see that 39.39% (B→A) of the respondents make choices in accordance with prospect theory. There is a preference reversal for the 39.39% of the respondents, as they prefer the lottery to the safe outcome in question 1, but the certain loss over the small chance to break even and large chance of breaking even. While 27.27% (A→A and A→B) of the respondents have preferences as predicted by expected utility, the difference in respondents do a reversal after answering A depends on the person's risk aversion 33.33% (B→B) of the respondents have preferences that cannot be explained by neither prospect theory nor expected utility. This could be explained by the respondents failing to understand the question.

The intention behind questions 2 and 4 was to obtain exact data in order to determine the degree of probability weighting for gains gamma value and losses delta value of probability weighting. It is evident from the values obtained that the respondents misunderstood or misinterpreted the question, as most of them failed to provide the correct responses (for instance, assigning a higher probability than 1% for “x” in question 4, but still preferring a safe loss to a gamble when faced with the same situation in 3). If the values had been correct, then it would be possible to give better advice to each respondent. This would not be a problem for a wealth manager, who in an advice process would help the client and understand the more complicated questions, such as questions 2 and 4 of this survey.

5.2 Mean-Variance Efficiency or Preference for Skewness

Although the first four questions test preference for skewness in a lottery payoff, we included a question to test preference for skewness over mean-variance efficiency. The respondents could choose between lottery A, with payoffs of 4,000 NOK with a probability of 40% and 5,000 NOK with a probability of 60%, or lottery B, with a payoff of 4,200 NOK with a probability of 98% or 10,000 NOK with a probability of 2%. These lotteries were deliberately chosen such that lottery A was negatively skewed, but with a higher mean and a lower standard deviation than lottery B. Although lottery B is not mean-variance efficient, the lottery has a positively skewed payoff distribution.

The respondents were divided into subgroups by first taking the subgroup of the respondents who hold equity, and then dividing this group into two subgroups of those who only hold funds and those who only hold stocks. Prediction from idiosyncratic skewness puzzle by Barberis and Huang (2008), the article predicts there will be preference for skewness and respondents would prefer lottery B. Lottery A shares many of the characteristics of a passive market fund, which is mean-variance efficient, but negatively skewed. Lottery B shares the characteristics of a portfolio of an undiversified investor with high preference for skewness.

Table 5.2.1 – Preference for skewness

	Lottery A	Lottery B
Expected return	4600 NOK	4316 NOK
Standard deviation	489.85	820.07
Skewness	-0.41449	6.889773

As the table below suggests, those who only hold stocks prefer more skewed payoff than those who hold stocks and funds or only hold funds. Of the respondents who hold stock and fund or only fund, 74.10% prefer lottery A, while 25.90% prefer lottery B. This stands in contrast to those who only hold stocks, as 54.55% prefer lottery A and 45.45% prefer lottery B

Table 5.2.2: Preference for skewness among equity holders

	Lottery A	Lottery B
Preference among all participants	52.20 %	47.80 %
Diversified equity holders (fund and stock holders with funds) N=27	74.10 %	25.90 %
Undiversified equity holders (only stock) N=11	54.55	45.45 %

We also discovered interesting findings in the level of diversification among stockholders in the choices of lotteries. There are considerable differences in the number of stocks held in the portfolio among those who prefer lottery A to lottery B. Respondents with stock only equity exposure have less than 4 stocks on average. While respondents with equity and stock exposure have considerably more stocks and funds to obtain diversification. This should be interpreted as such that stock holders choose lower diversification by investing in a few stocks rather than funds or a broad portfolio. We did not test the relationship any further as there were very few respondents for the group with stock only equity exposure. Only 11 people had stock only equity investments. With a survey with more respondents this would be very interesting relationship to investigate. We urge researchers to investigate this further.

5.3 Probability Estimation

In the survey, the respondents were asked to provide estimates of the probabilities of the OBX index falling 20% and 40% within a year. The respondents were also asked to estimate the probability of the index having a value 20% and 40% lower than today's value in exactly one year. Estimating these probabilities is assumed to be an important factor of how attractive equity is, regardless of the person being mean-variance investor, expected utility or prospect theory.

We calculated the actual probabilities based on historic data from the OBX index since 2001. Fifteen years of historical data is limited, and actual probabilities could thus be somewhat different from the following calculations.

Respondents have remarkable high accuracy in providing estimates, as estimates are very close to actual probabilities. However, there are large differences in probability estimates among equity holders and non-equity holders. We have divided the results of the probability estimates into equity holders and non-equity holders in order to utilise these differences in the advice section. Where equity holders own stocks or funds.

The survey provides evidence that probability estimation is important in determining the attractiveness of investing in equity. Interestingly, the results show that equity holders consistently estimate lower probabilities for medium and large downfalls than those who do not hold equity. Furthermore, non-equity holders predict in 3 of 4 estimates that the frequency of large fall in the index as more frequent than they actually happen. The upward-biased estimates are largest for the extreme outcomes, while equity holders in 3 out of 4 estimates naively estimate the probability to be lower than the actual frequency. These results suggest that misestimating could be a contributing factor to why people hold equity or not.

Table 5.3.1 – Probability estimates for negative fluctuations on OBX index within a year

	Real probability		Estimate all		Estimate non stock and fund holders		Estimate stock and fund holders	
	80 %	60 %	80 %	60 %	80 %	60 %	80 %	60 %
OBX Index below at some point within a year	33.33 %	13.33 %	24 %	12.70 %	30.70 %	19.40 %	18.50 %	7.14 %
Standard deviation			20.30 %	15.60 %	23.20 %	19.50 %	16.50 %	8.80 %
Number of respondents			67	64	30	29	37	35

Table 5.3.2 – Probability estimates for negative fluctuations on OBX index within exactly one year

	Real probability		Estimate all		Estimate non stock and fund holders		Estimate stock and fund holders	
	80 %	60 %	80 %	60 %	80 %	60 %	80 %	60 %
OBX Index below at some point within a year	20.00 %	6.40 %	18.7 %	9.30 %	18.70 %	15.10 %	16.40 %	4.90 %
Standard deviation			20.20 %	13.10 %	17.30 %	17.50 %	22.80 %	5.90 %
Number of respondents			67	64	30	28	37	36

We wanted to test if there existed a statistical significant difference between the group with experience with stocks or fund and the group with non-experience, on the perceived frequency of medium and large negative fluctuations on the OBX index. We tested both for fluctuations leading to lower value of 20% within a year and 40% within a year. We also tested for fluctuations leading to 20% lower index values in exactly one year and 40% lower index values in exactly one year.

We used Excel to calculate a two sample t-test where assuming equal variance. We assumed equal variance since the variance between the group were relative small.

The null hypothesis for the t-test was that the population's means from the two unrelated groups were equal:

H_0: U_1=U_2

The alternative hypothesis for the t-test was that the population's means are unequal.

$H_1 = U_1 \neq U_2$

The significant level that allow us to reject the null hypothesis and accept the alternative hypothesis was set to 0.05.

The result from the t-test indicates that we can reject three of the four null hypothesis, which indicates that the population mean is unequal. For estimates on the probabilities for index value reduced by 20% within a year, index value reduced by 40% within a year and index value reduced by 40% in exactly one year the estimates are significantly different. Respondents with experience in equity investment assigned significantly lower estimates than respondents without this experience.

The t-test showed in table 5.3.5, estimates for the frequency of a 20% lower index value in exactly one year, could not be rejected on a 0.05 significance level, since the t-value is below the critical value.

Table 5.3.3 – OBX Index value of 20% lower within a year

t-Test: Two-Sample Assuming Equal Variance

	Variable 1	*Variable 2*
Mean	0.3073333	0.1854054
Variance	0.0537513	0.0271644
Observations	30	37
Pooled Variance	0.0390262	
Hypothesized Mean Difference	0	
df	65	
t Stat	2.5121694	
P(T<=t) one-tail	0.0072455	
t Critical one-tail	1.668636	
P(T<=t) two-tail	0.014491	
t Critical two-tail	1.9971379	

Table 5.3.4 – OBX Index value 40% lower within a year

t-Test: Two-Sample Assuming Equal Variances

	Variable 1	*Variable 2*
Mean	0.1936207	0.0714
Variance	0.0378519	0.0076986
Observations	29	35
Pooled Variance	0.0213162	
Hypothesized Mean Difference	0	
df	62	
t Stat	3.3337477	
P(T<=t) one-tail	0.0007247	
t Critical one-tail	1.6698042	
P(T<=t) two-tail	0.0014494	
t Critical two-tail	1.9989715	

Table 5.3.5 – OBX Index value 20% lower in exactly one year

t-Test: Two-Sample Assuming Equal Variances

	Variable 1	*Variable 2*
Mean	0,1871	0.186297297
Variance	0.029784231	0.051838381
Observations	30	37
Pooled Variance	0.041998837	
Hypothesized Mean Difference	0	
df	65	
t Stat	0.015942638	
P(T<=t) one-tail	0.493664495	
t Critical one-tail	1.668635976	
P(T<=t) two-tail	0.987328989	
t Critical two-tail	1.997137908	

Table 5.3.6 – OBX Index value 40% lover in exactly one year

t-Test: Two-Sample Assuming Equal Variances

	Variable 1	*Variable 2*
Mean	0.150607143	0.048694444
Variance	0.030635507	0.003192333
Observations	28	36
Pooled Variance	0.015143392	
Hypothesized Mean Difference	0	
df	62	
t Stat	3.286676764	
P(T<=t) one-tail	0.00083585	
t Critical one-tail	1.669804163	
P(T<=t) two-tail	0.0016717	
t Critical two-tail	1.998971517	

5.4 Overconfidence

The accuracy of the estimates indicates that people assign to their estimates confidence intervals which are too narrow. The actual confidence in the estimates for the whole sample is 68% for Switzerland and 59% for Papua New Guinea, which is less than the 90% that the respondents were asked to provide. This is indicating overconfidence among the respondents.

As most of the respondents are from Europe, it seems fair to assume that the respondents are more familiar with Switzerland than Papua New Guinea, since Papua New Guinea is a more distant country. Most of the respondents should thus have better knowledge about the true population of Switzerland, and thus include a wider confidence interval to Papua New Guinea than to Switzerland to account for this. Confidence intervals are 23% wider on average for Papua New Guinea, should be “even” wider to take account for the true uncertainty in the estimates.

We divide the sample between those who believe that they have the ability to beat a broad index and those who do not think that they have this ability, or are uncertain whether they have this ability. This could be interesting from a wealth manager point of view, as the degree of overconfidence could lead to active trading. From the data we have obtained, this is not confirmed, as both samples have very similar estimates, and the ones who believe they are able to outperform the index have slightly higher confidence in their estimates. They have a confidence of 60% for Papua New Guinea and 70% for Switzerland, compared to those who do not have or are uncertain they have this ability, who have a confidence of 59% and 68%, respectively.

The Perceived Relative Importance of Investment Factors

In the survey, the respondents perceived the relative investment factors in the following manner.

Table 5.4.1 – Perceived relative importance

Market timing	22,61%
Product selection	26,06%
Investment strategy	51,03%

Market timing was defined as the “short run over and underweighting of asset classes”. Product selection was defined as the “the product selection within each asset class”. Investment strategy was defined as the “long-term assignment of wealth to asset classes”. The perceived importance matters to the wealth management process, as will be discussed in the advice section.

5.5 Weaknesses of the Survey and Further Research

As discussed earlier, the validity of the report might be questioned as we deliberately chose to focus on students in economics, business, strategy, and finance, instead of a group that is representative of the population. The study is easily replicable, and we encourage others to obtain similar data on other groups to test the population.

From the data obtained, we see that the respondents did not fully understand questions 2 and 4. The design of the question might have been too complicated, as people assigned values of "x" that were too high, and there is very little consistency between the questions. Questions 1 and 2 are similar, but question 2 is designed to obtain exact gamma values, while question 1 is designed to see if people's weighting of probability is larger or smaller than on a scale of γ=0.8470. Similarly, question 4 is designed to obtain an exact value of the probability weighting for losses, while question 3 is designed to see if people's probability weighting is larger or lower than the value of δ= 0.8470. If similar questions are used in further research, or in a diagnostic tool, researchers should provide further guidance to respondents on how to answer these questions correctly.

Lack of incentive compatibility might partially explain why 12 people did not complete all the questions in the study. The average time spent on the survey was 12 minutes. However, looking at the surprisingly high accuracy in predicting OBX returns, which requires qualified reasoning, we believe that the respondents did their absolute best in giving precise answers and providing detailed and accurate information. The experiment is easily replicable and could be used by researchers, with the possibility of incentivising respondents to control for lack of incentives.

6 Advice – Investments Process

In this section, our intention is to go through an investments process, which is an example on how a wealth manager could structure his or her process in order to detect whether the client is affected by probability weighting. The advice provided at the end of this section builds on prospect theory, the literature review, and the empirical findings on probability weighting.

In section 6.1, we address the issue of how to use diagnostics to calculate behavioural parameters that are necessary for the wealth management process. In section 6.2, we discuss effects on the clients portfolio if the client have preference for positive skewness. In section 6.3, we provide advice on the investment strategy, and discuss how estimates of the perceived importance of investment factors and equity riskiness influence the wealth management process.

We employ the same definition of wealth management as Russ Alan Price, "*wealth management is the consultative process of meeting the needs and wants of affluent clients by providing the appropriate financial products and services*".

Wealth management distinguishes itself from private banking, as private banking is a broader category of services which are offered to high-net worth individuals, such as tax planning, inheritance advisory, concierge, and wealth management. The definition highlights that wealth management is a narrower category. Wealth management is limited to the consultative process of meeting the needs and wants by providing financial products and services. Private banking includes wealth management, but is not limited to wealth management services.

As this is a thesis in behavioural finance, we are more interested in the wealth management process than the other services which are offered by private banking.

Wealth Manager vs. Financial Engineer

The clients' needs and wants may change over time. Similarly, the financial markets are subject to continual changes and complexity. For the bank to update new information, specialisation is needed. A natural way to structure the wealth management process for the bank, is to have personnel who is specialised in the client advisory process and others who are specialised in financial markets, which can supply the bank with high-quality financial products. (Hens and Bachmann, 2011)

We define financial engineering as the application of innovative financial technology to provide investors with preferred financial products, by employing financial technology, including financial theory, financial processes, and quantitative techniques to develop financial products for investors.

The Importance of a Standardised Approach and Routines

Hens and Bachmann (2011) explain the importance of standardised approaches when performing diagnostics of the clients and providing advice to the clients. Standardisation is important to ensure that advice are objective and do not reflect the advisor's own preferences. By employing standardised approaches and routines, the clients obtain the same advice regardless of who is the bank's wealth manager. This would then improve the trust between the client and the bank.

It is also crucial to be aware of the fact that the wealth manager could make mistakes relative to probability weighting. The wealth manager might have biased expectations of asset classes, such as stock or bond, etc. Therefore, it is necessary for the bank to have a standardised approach and routines in place to provide advice to the clients and be able to learn as an organization.

In addition to probability weighting, researchers have discovered many other biases which could lead to investment mistakes. A standardised approach is also important in accounting for these behavioural biases. However, in this thesis the focus has been on probability weighting and close relative concepts. Therefore, the advice will be related to how wealth managers need to understand the clients who have prospect theory probability weighting.

A prerequisite to a standardised approach is to utilise the modern diagnostic tools of behavioural finance. Diagnostics could be used to quantify the needs and wants. Quantifying is important, as a qualitative process can lead to multiple interpretations, and the bank requires quantitative data.

6.1 Diagnostics

The most important part when providing investment advice to customers is to understand the customer and the customer's goals. A standardised wealth management process should use the asset-liability framework to discover the needs of the customer. The framework's intention is to help the client distinguish between asset, which should cover the obligation, and “free” asset, which the client could apply for a specific goal.

The customer is interested in high return and low risk, but normally the customer is not always fully aware of the potential biases he or she is be subjected to. Biases and mistakes might lead to inconsistencies in investment strategies, and inconsistencies can be very expensive. Furthermore, the literature review and the empirical findings document that skewed assets are oversold. Clients with insufficient diversification hold positively skewed stocks. As described in the literature review, Barberis and Huang (2008) derive that people prefer higher moments on the return distribution rather than expected return and variance.

Private banking and wealth management are based on long-term customer relationships, ensuring long and profitable relationships. The wealth manager needs to build a bridge between the client and the market. Advice must be based on decision theory. However, the choice of theory is of importance to the investment allocation. Decision theory gives very different advice to the same person. A modern wealth manager needs to find the theory that best captures the characteristics of the client. Mean variance and subjective expected utility framework neglect the preference for skewness in return distribution, while prospect theory captures this property through the probability weighting function, as people use decision weights with transformed probabilities. The wealth manager should have knowledge about the customer’s probability weighting since this is important in the decision-making process.

The intra study (Marc Oliver Rieger, 2011) documents that probability weighting differ substantially between cultures, gender, and wealth. Wealthier countries weight probabilities less. Women show stronger probability weighting than males. The large variances in probability weighting on the aggregate suggest there are even larger variances in probability weighting on the individual level. In order to provide tailor-made advice and match preferences for different outcomes, it is important to use diagnostics to find the degree of probability weighting.

The survey shows that probability weighting is common: 73.52% (50/68) of respondents have a gamma value of 0.8470 or less. The gamma value is obtained from the implied gamma value from valuing lottery (answer B) over certain gain in question 1. Of the 73.52% of respondents, 47.80% (32/67) have an implied gamma value of 0.648 or less, by preferring lottery B to lottery A in question 5. As almost half of the respondents have probability weighting approximately on the same magnitude as the median parameter values of Kahneman and Tversky, even educated people with numerical reasoning distort probabilities. Probability weighting should thus be seen as a preference.

There are computer tools available to find gamma values for individual clients. Using these tools to determine the degree of probability weighting as measured by gamma values can be done cost-efficiently, and provides wealth managers with important information which can be used to determine the right investment strategy. This could lead to an improvement for the bank in the form of more satisfied customers, because the advice given to the customers take into account that the customers do not understand their own biases and mistakes. If the wealth managers do not understand how the customers see probabilities, this could lead to inappropriate advice.

Wealth managers can use questionnaires or trading simulations to derive the right utility function of the clients' ex ante of their investments. Questions similar to the four first questions of the questions in the survey may help the financial advisor to determine the degree of probability weighing.

From questions like this, it is easy for wealth managers to derive gamma values that can be used in the assessment of which products best suit the client.

6.2 Trade of Between Skewness and Efficiency

The behavioural finance literature suggest a trade-off between skewness and mean-variance efficiency among investors. The behavioural finance literature provides a plausible explanation to the idiosyncratic volatility and idiosyncratic skewness puzzle. Our survey could be seen as confirming that skewness preference explains these puzzles. Several participants, even those who hold equity, are willing to accept a 67% higher standard deviation and a 6% percent lower mean to obtain a skewed payoff.

The findings in the reviewed literature, as well as our own findings, with evidence supported by literature, suggest that skewness preference have major implications in the advisory process. Wealth management has traditionally been based on expected utility and mean-variance efficiency, neglecting preference for skewness. In the mean-variance framework, the optimal allocation is given by the two-fund separation theorem, holding a proportion of the market index and a risk-free asset. This might not be optimal seen from the probability-weighting client's point of view, as the market is negatively skewed in aggregate. Wealth management based solely on mean-variance efficiency will thus fail to provide a large part of clients with products that match the preferences of the clients. This raises a fundamental question of whether probability weighting is rational or not? Should wealth managers provide products that are based on the preferences of the client, or should wealth managers provide mean-variance efficient products?

Contrasting probability weighting with probability misestimation helps to answer the question. Probability misestimation is clearly irrational as one fails to assign the correct beliefs or update probabilities in a Bayesian way. Probability weighting on the other hand, as discussed earlier, is about choice when objective probabilities are known. It is about valuing certain states in the decision phase more than others, which is a preference.

Because probability weighting is caused by preference for lottery-like payoffs, wealth managers should consequently provide products that match the preference for skewness. As the general discussion below shows, there are multiple ways to add skewness to a portfolio, which should be more financially sound than under diversification or holding high-volatility assets with skewness, as the literature demonstrates is very common.

6.2.1 Structured Products to Increase Skewness

To evaluate which structured product is optimal for the client, it is important to distinguish between two different approaches, yielding different results:

- Evaluating the return distribution of the underlying product under probability weighting
- Evaluating the return distribution of the structured product under probability weighting

Both approaches can be justified, but the choice of model determines the product that is advised. The former approach, were evaluating the return distribution of the underlying the utility increases monotonically with the underlying and products and clients will value call option like payoffs of the underlying. Taking the second approach, straddles are advised, as extreme payoffs are valued highly in the structured product. The weighting of extreme payoffs makes straddles attractive, even if the belief of volatility is not different from the market.

Which is the usual reason for buying straddles. Call options and straddles enhance skewness to a client's portfolio.

In order to assess how much to allocate into different assets, or to optimise products into accounting for all the behavioural parameters of the clients, including but not limited to probability weighting, is extremely difficult and way beyond the scope of this thesis.

The general advice in this thesis is to add certain elements, either products or single derivatives to an efficient portfolio to add skewness, but protecting capital in a mean efficient manner by a passive investment. The core should be placed in mean-variance efficiency products and an amount should be placed to achieve more skewness.

6.2.2 Portfolio Insurance

Theory suggests, and our survey confirms, that a large part of the population have prospect theory preferences to small-probability large-outcome lotteries. Preferring lower-expected-value to certain losses in lotteries with a small probability of large losses and a high probability of breaking even. Such preferences have major implications in portfolio optimisation. For such preferences, holding lottery components and portfolio insurance in the same portfolio simultaneously could actually be optimal. Products containing both lottery elements and portfolio protection, accommodating such preferences, are very complex and will entail large transaction costs. Products of this sort will be composed of several different assets, most positively including illiquid derivatives which will be very costly to obtain.

For the wealth manager, portfolio insurance should not be viewed only from the perspective of probability weighting, it should also be determined in regard to loss aversion.

6.2.3 6.2.3 Limitations of Lottery Questions

Although the questions used in the diagnostics can be used to estimate the behavioural parameters of prospect theory, there are limitations to using such questions to form portfolios. The limitation comes from the fact that lottery questions have only two outcomes, while assets in a portfolio normally have more than two outcomes. Questionnaires with more than 2 outcomes would lead to complexity in the diagnostic process it is still better to use questionnaire with two outcomes and use approximations to real parameter values.

6.3 Investments Strategy

We define investment strategy parallel to Thorsten Hens: “Investments strategy is defined as the long-term assignments of wealth to assets classes”. (Thorstein Hens, 2011)

To succeed over time, the investor will benefit from a long-term investments strategy. An investor that commits to a long-term strategy can better handle the market movements. A functioning investment strategy will guide the client in which actions to take when situations arise, such that decisions become mechanical and thus are free from biases. Changing strategy can be very costly. Perhaps two of the largest benefits of using a diagnostic tool to understand the behavioural parameters of the clients’ ex ante investing is in the understanding of how people react to changes in the market, and thus helping wealth managers know how to de-bias investors. The other advantage is being better able to develop an investment strategy that better suits the client, such that the strategy helps the client commit to the strategy.

We will briefly discuss the relative importance of asset allocation compared to security selection and market timing.

6.3.1 Importance of Asset Allocation, Security Selection and Market Timing

Financial economists disagree on the relative importance of asset allocation, security selection, and market timing when explaining the long-term return of a portfolio. Ibbotson and Kaplan (2000) and Xiong et al. (2010) find that most of the return comes from the market return. By market return Xiong et al. (2010). mean “*equally weighted return for a given period for all the funds in the applicable universe”.* As Ibbotson (2010) explains, in 2008, almost all funds went down despite their allocation strategy or active management. After moving market return from the regression, Xiong et al. results show that within a peer group, asset allocation and security selection or active management are of equally importance.

In the article “The relative Importance of Asset Allocation and Security Selection” by Assoé et al. (2006), they arrive at a similar conclusion as Xiong et al.(2010); that asset allocation and security selection on average are of equal importance. However, the importance is largely time dependent. Assoé et al. find that the asset allocation had relatively higher impact on overall return during the market crash in 1987. While security selection played a relatively more important role during the high-tech bubble (1999–2002).

Renato Staub and Brian Singer (2011) finds the relative importance of asset allocation, is between 2/3 and ½ depending on free scalability.

In the survey, we found that respondents perceived the asset allocation explains half the long-term return of an investment. Which is consistent with the literature. However, market timing is seen as disproportionally important.

Among the respondents in the survey, we found that respondents believe that on average 23% come from market timing for a 10-year investment. This seems to be an exuberated importance of market timing.

Market timing and active product selection require substantial knowledge of finance. If skewness preferences are met with skewed payoffs using lottery components as discussed, clients might be more inclined to accept passive products for the core of the investment, and thus it might be possible to gain from product selection compared to the low-returning equity with skewed payoffs in the literature that underperforms the market.

6.3.2 Estimation of Equity Riskiness

In the survey, we found different probability estimates among equity holders and non-equity holders for declines in the OBX index. Estimates provided by the entire sample provide estimates of equity riskiness seem to be very accurate. However, for all risks in question, equity holders perceive risks of major falls in the index as less frequent than those that do not hold equity. This could indicate that perception of risk matter to the attractiveness of different asset classes, not just the weighting of probabilities. However, there could be other explanations, such as differences in wealth or income, etc.

For the non-equity holders, it is the frequency of the most severe downturns that is most distorted. It is important to clarify that this is not probability weighting, but merely distortion of probability estimates. Probability weighting is decision weights when the objective probability is known, while here, respondents are asked to provide objective estimates of key risk probabilities. We see that objective estimates are biased.

The client's perception of riskiness matters to the attractiveness of different assets in the asset allocation. Wealth managers could possibly improve the attractiveness of holding equity simply by providing correct estimates of the actual probabilities in question. Our survey does not examine whether correct estimates would augment equity market participation or the sensitivity of better estimates to equity investment.

7 Conclusion

In this Master's thesis, we have explored probability weighting. The literature suggests that probability weighting is an important aspect of human decision making under risk. In our survey, we have found evidence to support the literature on behavioural finance in matters that are related to probability weighting. A large group of respondents prefers skewness to mean-variance efficiency, providing evidence which support the explanation of the volatility puzzle and the idiosyncratic skewness puzzle.

On aggregate, we find a surprisingly high accuracy in the respondents' ability to estimate key investment probabilities. However, the estimates are biased. Comparing equity holders and non-equity holders, non-equity holders predicts systematically higher probability for large declines than equity holders do.

We have formulated concrete advice and ways to structure the wealth management process seen from the bank to help probability-weighting clients. We emphasise the need for a standardised wealth management process, with routines and specialisation as well as the use of diagnostic tools to better understand the client.

We discussed the general implication of probability-weighting clients on asset allocation. Using lottery components in clients' portfolios to enhance skewness might be highly valued among probability-weighting clients. Similarly, portfolio insurance might be highly valued among clients. For probability-weighting clients, it might be optimal to hold both lottery components and insurance in the same portfolio.

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9 Appendix

Q1 - In the choice between a and b what would you prefer? A) A sure gain of 4000NOK B) A gamble with two outcomes. Either winning 200.000NOK with probability 1% or 99% probability of gaining 0.

Answer	%	Count
A	26.09%	18
B	72.46%	50
I would derrive the same utility from both options	1.45%	1
Unable to decide	0.00%	0
Total	100%	69

Q2 - In a choice where you have to choose either: a sure gain of 5 000 NOK, or a gamble with payoff 250 000 with probability x and payoff 0 with probability 1-x. For which value of x is the lowest value that you would prefer the lottery over the sure gain?

Field	Minimum	Maximum	Mean	Std Deviation	Variance	Count	undefined	undefined
value of X	0.00	0.97	0.28	0.26	0.07	68	undefined	undefined

Q3 - In the choice between a and b which would you prefer? A) a sure loss of 4000NOK B) a gamble With two outcomes. Either loosing 200 000 NOK With probability 1% or no loss with probability 99%

Answer	%	Count
B	47.83%	33
A	49.28%	34
I would derive the same utility from both options	0.00%	0
Unable to decide	2.90%	2
Total	100%	69

Q4 - In a choice between either: a sure loss of 5 000 NOK, or a gamble with a loss of 250 000 NOK with probability X, or no loss with probability 1-X. What is the HIGHEST value of X that you would prefer the lottery?

Field	Minimum	Maximum	Mean	Std Deviation	Variance	Count	undefined	undefined
Value of x	0.00	1.00	0.15	0.30	0.09	61	undefined	undefined

Q5 - Which of the following lotteries would you prefer? A) a lottery with 60% chance of gaining 5.000NOK or 40% chance of gaining 4.000NOKB) a lottery with 98% chance of gaining 4.200NOK or 2% chance of gaining 10.000 NOK

Answer	%	Count
A	50.72%	35
B	46.38%	32
I would derive the same utility from both options	1.45%	1
Unable to decide	1.45%	1
Total	100%	69

Q6 - How likely do you perceive the probability of the OBX index having a value that is equal or less than 60% of its current value SOMETIME WITHIN one year? (this is equivalent of the index falling from a value of 555 to a value of 333 or less within a year) - Probability of OBX loosing 40% or more of its current value sometime within a year

Field	Minimum	Maximum	Mean	Std Deviation	Variance	Count	undefined	undefined
Probability of OBX loosing 40% or more of its current value sometime withi...	0.00	0.74	0.13	0.16	0.02	64	undefined	undefined

Q7 - How likely do you perceive the probability of the OBX index having a value equal or less than 80% of its current value SOMETIME WITHIN one year? (This is equal of the index falling from a value of 555 to a value of 444 or less within a year) - Probability of OBX loosing 20% or more of its current value sometime within a year

Field	Minimum	Maximum	Mean	Std Deviation	Variance	Count	undefined	undefined
Probability of OBX loosing 20% or more of its current value sometime within...	0.00	0.82	0.24	0.20	0.04	67	undefined	undefined

Q8 - How likely do you perceive the probability of the OBX index having a value equal or less than 80% of its current value IN EXACTLY ONE YEAR? (For the index at 555 points, this is equivalent of the index falling to 444 in late May 2017)

Field	Minimum	Maximum	Mean	Std Deviation	Variance	Count	undefined	undefined
Probability of OBX loosing 20% or more of its value in exactly one year	0.00	1.00	0.19	0.20	0.04	67	undefined	undefined

Q9 - How likely do you perceive the probability of the OBX index having a value equal or less than 60% of its current value IN EXACTLY ONE YEAR? (for the index at 555 points this is equivalent of a value less than 333 or less in late May 2017)

Field	Minimum	Maximum	Mean	Std Deviation	Variance	Count	undefined	undefined
Probability of OBX loosing 40% or more of its value in exactly one year	0.00	0.76	0.09	0.13	0.02	64	undefined	undefined

Q10 - What is the relative contribution of the following factors in explaining investment result for an investment with 10 years horizon? (please make sure they sum to 100%)

Field	Minimum	Maximum	Mean	Std Deviation	Variance	Count	undefined	undefined
Market timing: "Short term over/under-weighting of asset classes"	0.00	90.00	21.93	16.33	266.77	69	undefined	undefined
Product selection: "Product selection within each asset class"	0.00	80.00	25.57	16.36	267.56	69	undefined	undefined
Investment strategy: "Long term assignment of wealth to each asset class"	0.00	100.00	49.53	23.65	559.36	69	undefined	undefined

Q11 - Which asset classes have you invested in the last 12 months?

Answer	%	Count
Fund	39.13%	27
Stocks	39.13%	27
Options	2.90%	2
Futures	0.00%	0
Forwards	1.45%	1
Real estate	10.14%	7
Structured Products	2.90%	2
Commodities	0.00%	0
Other	2.90%	2
Have not invested in the past 12 months	43.48%	30

Q12 - Did a wealth manager/ private banker use a diagnostic tool to assess which structured product suited your preferences?

Answer	%	Count
Yes	50.00%	1
Do not remember	0.00%	0
No	50.00%	1
Total	100%	2

Field	Minimum	Maximum	Mean	Std Deviation	Variance	Count	Bottom Box	Top Box
Did a wealth manager/ private banker use a diagnostic tool to asses which s...	1.00	4.00	2.50	1.50	2.25	2	100.00 %	100.00 %

Q13 - Describe shortly the investment strategy: E.G momentum strategy, value strategy, buy and hold strategy

Describe shortly the investment strategy: E.G momentum strategy, value stra...
Buy and hold funds, otherwise small cap momentum
Buy and hold
Alfa stocks.
buy and hold strategy, occasional shorting
Buy and hold
Buy and hold
Value
no time pressure, the money can stand there as long as needed. Then sell when lucky
buy and hold
Buy and hold
Momentum strategy
Value strategy
Did a quality-momentum investment strategy based on high quality assets in interesting industries would continue to preform well. options to get higher gearing
Momentum: Buy when the stock have increased the last 6m, and sell (or short) the stocks that have dropped the last 6m. Value strategy: buy companies with high
Yield strategy
buy and hold strategy
Buy and hold. Diversify.
1: Outperforming stocks continue to outperform. 2: I don't know. 3: Buy and hold long term investments
Buy and hold
Value and growth
Mostly investing in IPOs, with a buy and hold strategy.
buy and hold

Q14 - All thing considered, did your investment strategy outperform a buy and hold strategy of holding a diversified fund or holding the index?

Answer	%	Count
Yes	55.56%	15
Unsure	22.22%	6
No	22.22%	6
Total	100%	27

Q15 - How many stocks did you hold in your portfolio?

Field	Minimum	Maximum	Mean	Std Deviation	Variance	Count	undefined	undefined
Number of stocks	0.00	15.00	5.19	4.91	24.08	27	undefined	undefined

Q16 - Please assign upper and lower values of the population of Papua New Guinea in order to give an interval that with a 90% probability include the true value.

Field	Minimum	Maximum	Mean	Std Deviation	Variance	Count	undefined	undefined
lower Level of 90% confidence interval	0.00	130.00	15.78	24.24	587.58	64	undefined	undefined
upper Level of confidence 90% interval	1.00	150.00	51.25	44.10	1944.86	65	undefined	undefined

Q17 - Given your financial knowledge, and ability to pick stocks: how confident are you that you could construct a portfolio that could outperform an index like OBX over a 10-year period?

Answer	%	Count
I am confident that I could construct a portfolio that outperforms the OBX	14.49%	10
Unsure if I have this ability	37.68%	26
I do not have the ability to construct such a portfolio	47.83%	33
Total	100%	69

Q18 - Please assign upper and lower values of the population of Switzerland in order to give an interval that with 90% probability include the true value.

Field	Minimum	Maximum	Mean	Std Deviation	Variance	Count	undefined	undefined
Lower Level of 90% confidence interval	0.00	121.00	9.61	15.74	247.85	62	undefined	undefined
Upper Level of 90% confidence interval	3.00	150.00	39.12	41.86	1752.14	65	undefined	undefined

Q19- Gender

Answer	%	Count
Male	63.77%	44
Female	36.23%	25
Total	100%	69

Q20 - What age

Field	Minimum	Maximum	Mean	Std Deviation	Variance	Count	undefined	undefined
Years	0.00	34.00	23.81	4.62	21.31	69	undefined	undefined

Q25 - Educational background

Answer	%	Count
Master in Finance/Economics/ Strategy/ Business/	69.57%	48
Bachelor in Finance/Economics/Strategy/Business	30.43%	21
Bachelor in other studies	0.00%	0
Master in other studies	0.00%	0
PHD in other studies	0.00%	0
PHD in Finance/Economics/strategy/business	0.00%	0
other	0.00%	0
Total	100%	69

Q26 - Country of birth

Country of birth

Norway	58
Sweden	2
Germany	4
Australia	1
Tajikistan	1
USA	2
South Africa	1