MASTEROPPGAVE

Emnekode: EK371E **Navn på kandidat**: Yevheniia Antoniuk

Roman Zherebko

Mutual fund performance

A study on the DNB and ODIN mutual fund families

Dato: 17.05.2016 Totalt antall sider: 39

NORD universitet

www.nord.no

ACKNOWLEDGEMENTS

The submission of this thesis marks a very special bottom line in a last few years of our work. It has rewarded us with achievements regarding academic, professional and personal successes, but also given us a challenges to face and overcome.

For us, the most important is that we did a work that we were interested to do. Our research has revealed lots of problems in the mutual fund system itself, and some approaches to address those problems. This means that we now understand how further researches should be done and which direction to head them.

We would like to thank Nord University for the opportunity to create this thesis, and therefore fulfill our ideas and theories within prospect of this work. This submission will serve as an end of master students chapter for us, and will become a first step on our way to higher scientific degree.

Our biggest gratitude we would like to address to our supervisor, Professor **Svein Oskar Lauvsnes** , as it was his professionalism and qualifications that helped us to maintain this work on the rails of high-quality standards and interesting discoveries; Professor **Thomas Leirvik**, for guidance in unstable variety of problems that exists around Norwegian finance market analysis, specifically mutual fund market problems.; **Nito Simonsen** and **Maria Hadsel Olsen**, DNB asset management specialists, for explaining the backstage of real fund family functioning; **Martin Henrichsen**, ODIN sales director, for general reflection to the problems that we could not solve, without a person from inside the family fund system.

At last but not least, we would like to thank our colleagues and teachers in HHB department, for help with probably the hardest thing – motivating us to get the effective and interesting discoveries and results.

Time, is probably the biggest precious we possess, and people mention above were very generous to share it with us

The final results of our study are given below for your judgment.

Roman Zherebko ***Yevheniia Antoniuk***

PREFACE

We have done our research in order to analyze whether a mutual fund investing system in Norway is efficient and open to its clients. The idea was to estimate unrevealed problems through correlation and portfolio analysis process and optimize it using econometric instruments if that would be possible. Discoveries and suggestions given in this study are aimed to enhance productivity of biggest mutual fund systems in Norway who were in contact with us throughout the writing process.

SAMMENDRAG

I denne masterstudien har vi sett på to aksjefondet familier i markedet. Vi presenterer empiri som viser at fondene har sterkere korrelasjon innad, enn hva man finner mellom familier, noe som indikerer skjult risiko. To indeksmodeller og tre faktormodeller ble brukt som instrumenter for å undersøke risikofaktorene i portfolioene som ble presentert til investorer. Etter å ha analysert risikofaktorene, gjorde vi en portefølje optimalisering. Gjennom bruk av effektive «efficient frontier» og tagencyportefølje prosedyre, utarbeidet vi en ny kombinasjon av porteføljen.

ABSTRACT

This thesis provides an analytical study of performance within two biggest Norwegian mutual fund families on the market. At first, we have found evidence that the mutual funds are much more correlated within than between fund families, and therefore have hidden risks. Two index models and three-factor models were used as our instruments to study risk factors of the portfolios provided by the family holders to the investors. When that was determined, we introduced a portfolio optimization procedure. Eventually, through the use of efficient frontier and tangency portfolio approach, a set of new combination portfolios was created.

TABLE OF CONTENT

1 Introduction 1
1.1 Problem statement 1
2 Theoretical discussion 2
2.1 Net Asset Value as starting point 2
2.2 Performance measures 3
2.3 Background for portfolio optimization 5
2.4 Modern study on mutual fund performance 6
2.5 Banks as mutual fund owners 9
2.5.1 Family of mutual fund 9
2.5.2 Aiming of fund family 10
3 Method 11
3.1 Approach 11
3.1.1 Returns 11
3.1.2 Correlation 12
3.1.3 Assumption for regression 13
3.1.4 t-test 14
3.1.5 Optimization process 15
3.2 Data collection 17
4 Practical mutual fund functioning 18
4.1 DNB family of mutual fund 19
4.2 ODIN family of mutual fund 23
4.2.1 Combination funds 23
5 Findings 25
5.1 Descriptive statistics 25
5.1.1 Correlation within and between fund families 25
5.2 Portfolio analysis 28
5.2.1 Tangency portfolio of two mutual funds 28
5.2.2 Efficient Frontier 30
6 Summary 33
7 Literature list 35
8 Appendices 39

LIST OF TABLES

Table 5-1. Average monthly return and risk by type of the mutual fund (whole period) 25
Table 5-2. Return correlation by the type of the mutual fund within and between fund family 26
Table 5-3. Determinants of the differences in fund correlations within and between families 27
Table 5-4. Comparison of the portfolios – the combination funds against tangency portfolio (two assets) 29
Table 5-5. Comparison of the portfolios – the combination funds against tangency portfolio (unrestricted number of assets) 32

LIST OF FIGURES

Figure 1. Stocks of mutual funds shares by type as of 30th September 2015 (Market value in NOK Billion) 18
Figure 2. Structure of the mutual funds' investment by instruments (2016) 20
Figure 3. Country profile of the “Aktiv” mutual funds of DNB (2015) 22
Figure 4. Countries structure of the DNB stock funds 22
Figure 5. Country structure of investment by ODIN combination funds (2015) 24
Figure 6. Efficient frontier for DNB fund family (excluding the combination funds) 30
Figure 7. Efficient frontier for ODIN fund family (excluding the combination funds) 31
Figure 8. Efficient frontier for the fund families (excluding the combination funds) 31

List of equations

(2-1) Shape ratio definition 3
(2-2) Modigliani risk-adjusted performance measure 4
(3-1) Logarithmic return definition 12
(3-2) Transformation of a compound rate 12
(3-3) Covariance by definition 12
(3-4) Correlation definition 13
(3-5) Multiple regression by Fama-French model 13
(3-6) Student t-distribution 14
(3-7) t-statistic for slope testing 14
(3-8) t-statistic for the mean difference testing 15
(3-9) Degrees of freedom for the mean difference testing 15
(3-10) Maximization problem for a tangency portfolio (general) 16
(3-11) Assets' weights in a tangency portfolio with two assets 16

List of appendices

Appendix A Classification of the mutual funds and their assigned variable 39
Appendix B Descriptive statistics for the mutual fund families and market 40
Appendix C Correlation between funds 42
Appendix D Correlation between funds' residual 45
Appendix E Tangency portfolio of two assets for the mutual funds 48
Appendix F Efficient frontier for DNB 53
Appendix G Efficient frontier for ODIN 56
Appendix H Efficient Frontier for mixed funds portfolio 58
Appendix I Tangency portfolios assessment 61
Appendix J R script with code for master thesis 63

1 INTRODUCTION

Millions of investors every day are looking for a portfolio that will have the perfect balance of high profits, minimum risks, and significant liquidity. In every particular case, there will be a set of unique circumstances that can be crucial for investor no matter how common characteristics of a good investment are.

This master thesis focuses on a special type of the mutual funds – a family of mutual funds. A mutual fund family offers a range of portfolios (mutual funds) with a different objective, country orientation, industry specialization. The distinctive feature of such families is that they often are affiliated – i.e. launch mutual funds that invest in functioning one that is already owned by the family. We decided to take a closer look at two biggest fund families in Norway that are owned by bank: a family of DNB-owned mutual funds and ODIN-family, owned by SpareBank1. Both funds relate to fund family and are owned by the bank, which is really distinctive for the Norwegian market.

Mutual funds are relatively modern investment method and tend to be more and more functional and popular instruments of collective investment(Graham, 2003). Clients now have a possibility to actively dedicate to investments activities of the bank by joining in mutual funds. Such service will benefit clients as they get an opportunity to increase their revenues by more than average deposit while reducing inconvenience and lack of competence in investment process as the bank provides expert fund management and transparency upon making money in such way. They are handy for those who has a good understanding of stock funds' functioning, as well as among inexperienced private investors. Unlike investment companies, investment funds have no restrictions upon sources of resource allocation. They can be formed on behalf of ordinary people and target enhancing and improvement of investment activity on the secondary market of securities.

The banks organize subsidiaries that are in charge of a mutual fund management. These companies launch a wide variety of the mutual funds in order to meet all possible requirements of future investors. Thus, a family of the mutual funds is being established.

1.1 Problem statement

Changes in performance of one of the mutual funds inside the family will have its effect on other portfolios and we are going to show which direction and how strong such inter-family correlation will appear to be in two biggest Norwegian mutual funds family owners: DNB and ODIN.

Both funds suggest a rather broad variety of investment opportunities in order to please a wide range of possible investment strategies. While customers have access to 24 funds in a pool of DNB mutual fund family and more than 10 for ODIN, we will create a range of artificial funds which will be targeted to outperform funds that are prearranged by market leaders. By artificial portfolios, we mean portfolios, that include existing stocks and bonds funds. The main investigation object is existing combination funds – an investment offer, that combine stock and bond already. Our research will investigate whether portfolios provided by funds (combination funds) are the best offer within fund family and if we can find a better combination of stock/bond shares (given a comparison with OSEBX index).

We aim to compare a tangency portfolio, consisting of stock and bond mutual funds with existing combination funds of the families. So we want to look at possibilities, whether:

- it is possible to find portfolios within one family with higher a Sharpe ratio than the combination fund has, which is already owned by that family.
- it is possible to find portfolios, that includes assets from a different family and has higher a Sharpe ratio than family's owned combination funds.

Thus, in the beginning of the study we state the next hypothesis:

There exists such a portfolio of the stock and bond mutual funds, that overperform existed combination fund with the same weights of stock and bond in it.

2 THEORETICAL DISCUSSION

2.1 Net Asset Value as starting point

No matter, which type of securities a mutual fund holds, their value will be the result of a simple multiplication of security's numbers on current selling price on the market. After subtraction any liability, the mutual fund gets NAV. So what to do with illiquid bonds or that did not trade the day of NAV valuation? Wright (2003) mentioned a matrix pricing for this purpose. Nevertheless, the matrix pricing approach is suitable just for the fixed income market. Based on a primary explanation of Patrick Casabona and Robert Traficanti (2002) and Capital Management Group ("Bond Pricing: An Educated Guess," 2004), we can define it with the following algorithm :

- to divide all bonds under an assessment into the categories with a similar feature (a type of issuer, credit rating, maturity, coupon etc.);

- to define current risk-free rate;
- to describe all possible premiums in relation with bonds (default risk, management expenses, liquidity, option return, covenant and event protection, sector risk premium etc.)
- to sum up rate for identification of yield;
- based on calculated yields – defining of a bond price.

As for the close-end mutual funds, NAV is not a relevant indicator of a price, since close-end fund shares trade on the secondary market and have market-based pricing. Usually, this price is not equal to the intrinsic value of the share. Damodaran (2006) suggests using the amount of discount/premium as a reflection of fund ability to generate an excess return on investment.

Mutual fund returns are calculated on two basic components: NAV and a distribution of dividends and capital gain.

2.2 Performance measures

Usage of performance indices for evaluation the mutual fund management is a great and validated approach. There are three main performance indices: Sharpe's, Treynor's and Jensen's one. All three are the tools for ranking portfolio (and therefore the mutual fund in connection to each other).

Sharpe's performance index shows reward-to-variability ratio by the next formula:

$$S_i = \frac{ER_i - r_f}{\sigma_i} \qquad \textbf{\textit{(2-1)}}$$

where ER_i – expected return, σ_i – variance of portfolio i and r_f- risk-free rate. As given by Sharpe's ratio, the mutual fund manager earns better return than a market, when S_i for portfolio is greater than the market's one. The higher ratio (and therefore premium for 1% volatility), the better portfolio.

Jensen's index also compares the mutual fund's and market portfolio, but in absolute values. Actually, this index "measures the abnormal return of the portfolio of the mutual fund manager" (Cuthbertson, 1996, p. 59).

We find it relevant to define such approaches of measurement of the performance before reviewing major practical findings.

Shawky (1982) was mentioning , that all three indices give the same ranking among the 255 mutual funds during 1973-1977. This appears due to high correlation between β_i and σ_i. Pedersen and Vorland (2003), studying Norwegian stock mutual funds, got similar results: all indices give the same ranking for sample of the mutual fund. However, it is worth mentioning, that it is true based on the same year performance (same range of years' performance). It is impossible to predict next period rank for the fund.

Based on the performed studies on collected data since the 1960s and until 1990s, researchers' findings could be generalized as "The mutual funds got return not higher than the market did". Researchers of XX century postulated that:

- on average the mutual fund does not outperform the market;
- there is no technique to detect, whether the mutual fund in future will continue to earn more;
- the good mutual fund is a quiet mutual fund or, in other words, good performing fund does not need advertising to attract investors – such funds just earn money.

Modigliani ratio (or Modigliani Index, M2 factor) is an indicator reflecting the portfolio management efficiency. This indicator was proposed by Franco Modigliani in 1997 and allows to compare different investment options. Even though it is delivered from Sharpe ratio, Modigliani index avoids the downside of being "dimensionless" measure. It usually benefits over Sharpe ratio in case of negative returns: The Modigliani ratio continues to hold its meaning when Sharpe becomes hard to interpret

Among the broad variety of performance measure indicators, Modigliani risk-adjusted performance (or M2) is said to be one of the most representative. This indicator compares the yield of the fund with a yield of a passive strategy. This will have value in the case, where the standard deviation of the portfolio is reduced to a level, that is equal to the standard deviation of the market portfolio. A positive value of this indicator speaks of effective active management strategy and its performance in the portfolio.

$$M2 = \frac{(ER_i - r_f)\sigma_m}{\sigma_i} + r_f \tag{2-2}$$

Where σ_m is the standard deviation of a benchmark (market). One could use as the benchmark S&P500 index, the MSCI World index, or another broad index. So if portfolios excess return is proportionally higher than one of the benchmark, it would eventually have proportionally higher risk.

The higher value of M2 coefficient represents higher returns that investor gets in comparison to benchmark (risk-free active), at the given amount of risk, which is shown by the leverage. An investment that took significantly higher risk than benchmark portfolio, and had no corresponding performance advantage, would eventually have a lesser risk-adjusted performance by the Modigliani ratio and thus, be less promising for the investor.

Questions about mutual fund performance are a topic of interest to discuss because investors are interested in buying shares of the high-returning mutual fund. However, is there any tendency for a performance stability? Will outperforming mutual fund today repeat such result tomorrow? As Damodaran (2002) showed, there is no evidence to assume this. In a study of 1983-1990s data, all performance results were divided into quartile by a return. The researcher examined what the probability of moving from one quartile to another was. The study found that it is almost equal chance to get any return at any given starting position.

Carhart (1997) oppositely found some evidence of persistence of the performance for the extremes: small groups of the portfolio that show high return over a passive strategy and low return due to high expenses have a tendency to keep such performance.

Summarizing XX century findings, they have several common points: the average fund does not beat the market; the higher funds expenses, the lower return; if a mutual fund trades its stocks more frequently, it tends to get a lower return; high volatility funds tend to keep high volatility over time.

2.3 Background for portfolio optimization

The main target of portfolio optimization is to find the best risk/return combination. This can be achieved by adjusting of project (elements) parameters that are included in the portfolio. In order to reach this goal, creation of managerial recommendation upon projects transformation is required. This can be done by chaining all of the relevant projects (those that have shared targets, tight connection, and dependencies in the sense of having a common owner, shared resources or management) into groups and matching them inside groups. Set of questions should be created to each of such groups which would address projects, and conditions required to include them into the portfolio.

The goal of portfolio optimization is:

- Finding minimal risk at given expected return
- or, equivalently finding maximum return at the given level of risk

Eventually, those operations will narrow to MV (mean variance) optimization, which focuses control scope around expected return of the investment as a mean and its variance, as the measure of risk associated with the portfolio.

Determination of best portfolios among all of those advised is, in fact, the main problem of optimization and becomes the main goal of optimizing processes. The final decision would be lying on investors shoulders. Each case will be personal, depending on company type, market type, investors willingness to risk and targets that he wants to achieve. That does not mean that optimization process cannot be steady, moreover, optimization is a widely spread tool with rather linear task – making investors portfolio efficient.

Efficient portfolio (or an optimal portfolio), is a portfolio that is completed so that it reaches a certain expected return or a certain risk (variance). There are a lot of different methods for creating of such portfolio, that mainly depend on the level of risk that investor assumes as acceptable. The father of modern portfolio theory, Harry Markowitz, has assumed that with risk measured by standard deviation of the portfolio's rate of return, the investor would seek to maximize expected rate of return contingent to the given level of risk (Markowitz, 1952). To solve risk-return tradeoff problem within portfolio optimization, the distribution of risky assets random return must be found first. Markowitz formulation assumes, that risky assets can be distributed according to a multidimensional normal distribution $N(\mu, \Sigma)$, where Σ is a covariance matrix and μ is a vector of means and those are the grounds for solution of optimization problem (Palczewski, 2008).

2.4 Modern study on mutual fund performance

For the last 10 years, studies developed a variety of factors / approaches that could define the performance of mutual funds. Since researchers could not find some strong evidence about constantly outperforming mutual funds, they shifted the focus of study a bit.

Huang, Sialm and Zhang (2011) assumed that a persistence in the mutual fund activity could be measured by risk parameters, rather by abnormal returns. Researchers found out that funds with increased risk perform worse than one with stable risk level.

Monthly and annual data on the mutual fund returns could not define persistence in performance, therefore Bollen and Busse (2005) suggested that relatively short-term evaluation of the mutual fund could give a significant result. Bollen and Busse analyzed daily return of

230 mutual funds. They conclude that top decile of the mutual fund on average get an abnormal return at 25-29 basis point higher than a sample. Moreover, such abnormal return persists, when we look no longer as a quarter ahead based on daily returns.

Following such interesting results, Huij and Verbeek (2007) decided to repeat Bollen and Busse analysis on the larger sample. Taking into consideration monthly data, they compared 36- and 12-month persistence of performance. Findings showed that shorter horizon was able to predict future performance. Bayesian alpha as performance measure was more accurate – top decile mutual funds' earnings were significantly higher in the next period – they earned approximately 0.26 percent per month. However, only young small capitalization / growth funds had such characteristics.

Nevertheless, Carhart (1997) think that returns within one year are noisy and cannot be treated as a relevant performance measure. Vidal-Garcia (2013) considers this statement and makes the analysis of performance persistence over 2 and 3 years horizon based on 4-factor model (momentum is added to 3-factor Fama-French model). Finding revealed that persistence of positive returns become greater with increasing horizon (from 24 to 36 month), but significant negative persistence was observed for longer periods.

Scientific background for an understanding of portfolio construction, its performance and estimated future returns was established by Sharpe (Sharpe, 1964, 1970) and Lintner (Lintner, 1965). In some time after establishing of their CAPM model, the presence of many assumptions and shortcoming has led to its re-considering and further development by many scientists. Willingness to avoid shortcomings of CAPM model, its lack of risks factors that affects expected return, has stimulated the development of a new, multi-factor models for estimating returns of financial assets (Mossin, 1966).

Fama-French three-factor model is oriented to do a better risk assessment and has a different from CAPM approach to a market pricing explanation. The model assumes that investors in real market circumstances are interested in considering three separate risks factors related to the portfolio rather than just one.

Two other factors besides the market premium (Beta) that this model appreciates are size premium and value premium. The three-factor model defines the value premium as the difference in returns between the stocks with 30% highest BTM (Book to Market ratio) and the 30% lowest BTM while the difference in returns between the largest stocks and smallest stocks will form size premium (Armstrong, 2013).

Eventually, the three-factor model will result in a sum of next factors: zero risk return, market, size and value premiums, random error and management impact (Alpha).

Fama-French model advantages

Considering the higher amount of factors included, Fama-French model allows you a more precise modeling of price-establishing processes on the fund market. For example, it includes risks that are not included in the analysis of market (systemic) risks as they are associated with enterprise activities and therefore are related to the specific (idiosyncratic) risks of the company.

This model allows considering the possibility of multidirectional impact of innovation on a variety of risks which is, accordingly, reflected in both the increase and decrease in share prices;

Additional criteria that are introduced in Fama-French model allows considering industry specifics on different levels. This has a critical value in many instances, for example in enterprise innovation activity research, depending on industry relation to high or low tech branch, an investor can estimate investment amount needed and expected results from innovation implementation.

Major studies show that outperforming mutual funds exist when we measure their gross return, but after fee and trading costs subtraction, they get a negative return (Cuthbertson, Nitzsche, & O'Sullivan, 2010).

Independently Cuthbertson et al. (2010) and Barras et al. (2010) confirmed so-called Berk and Green equilibrium: around 75% of the mutual funds has zero-alpha performance. Even if their managers are skilled, all returns are lost in the mutual fund due to operational inefficiencies. Distribution between positive and negative performance persistence was also "stable": around 20-25% of the mutual funds constantly earn a negative return. Barras et al (2010) also noted, that percentage of truly positive alpha mutual funds was changing over time: in the 1990s, it was 14.4%, while in 2006 – just 0.6%. The concept of true alpha enables differentiation between unskilled and skilled managers with respect to negative or positive its value.

Taking to consideration Norwegian mutual funds, few interesting relationships revealed in financial thesis:

- There is no difference in return of private and bank mutual fund in Norway. Based on data 2002-2009, Moen and Rønning (2010) disproved Knut Kjær's statement, that private fund seems to have a higher return.

- The relationship between portfolio return of the mutual fund and advisor fee exists and it is negative. The advisor, who manages higher profitable portfolio, gets a lower payment for service. Sølverg (2010) explained that phenomenon by the theory of strategic pricing.
- Norwegian mutual funds (that are index mutual funds) mostly beat the market, represented by Oslo Børs (Hornenes, Nedrejord, & Pham, 2015).

However, an earlier study by Brustad and Aksjer (2013) shows that positive abnormal return is significant only for one out of 44 mutual funds in Norway. At the same time, cross-country analysis of performance shows, that geography of assets matters – the mutual funds with mostly local assets do better (Coval & Moskovits, 2001).

2.5 Banks as mutual fund owners

Banks become a mutual fund founders relatively recently. By launching a mutual fund, the bank gets a new income source for its customers. But it is probably not the only reason to do this. As Choong and Richardson (Choong & Richardson, 2014) mentioned, banks experience a slower growth in traditional bank products while the customers' structure changes significantly: the number of borrowers decreases during an increase in savings. This is connected to demography: today there are more middle-aged people than young one.

2.5.1 Family of mutual fund

Official publication by authorities as well as most available sources defines a family of mutual funds as : *"a group of mutual funds that share administrative and distribution system"* (U.S. Securities and Exchange Commission, 2010). The main described advantage of investing in fund family is an avoidance of fee payments, connected with a change in a mutual fund (generally, there is no fee for transferring money within one fund family). Another one is that mutual fund tends to create a family of funds with low correlation. The low correlation is an argument against going outside fund family with a diversification purpose (Elton, Gruber, & Green, 2007).

Research shows, that investor at first tends to define fund family and afterward to decide in which fund to invest within it. Such a decision is based on personal preferences of risk-taking, desired returns on investment, individual assessment of industry development or other insights (and – what is more common in the USA – investment in only one fund family is predefined by retirement program of a company).

In the same time, Elton, Gruber and Green (2007) mentioned, that portfolio managers within fund family have access to the same market research, have the same predefined corporate objective and style, therefore it is possible to get higher risk investment when one buys a share of the few fund within the family.

Additionally, there are so-called affiliated funds of mutual funds – a part of the fund family, that can invest ONLY in shares of other funds in the family.

2.5.2 Aiming of fund family

There is no statement in the prospectus about the internal goal of the fund with respect to the whole family. But many researchers tried to find some. Spitz (1970), Chevalier and Ellison (1997) and Sirri and Tufano (1998) examined relations between abnormal returns (both negative and positive) and inflows/outflows. They found that positive abnormal returns affect inflow more than negative outflow. This also resulted in the next statement: if the mutual fund has two options – to have two mutual funds either both with above-average returns or with highly positive and negative simultaneously – it decides to have the last option.

Guedj and Papastaikoudi (2003), Gaspar, Massa and Matos (2006), Bhattacharya, Lee and Pool (2013) studied relations between funds within a family. The main question is whether the big family fund cares about interests of its investors or acts in favor of total family income.

There is evidence, that family supports a mutual fund with an abnormal performance by increasing the inflows in it. Persistence performance can be an additional reason for such decision. Winning mutual funds, therefore, get resources that do not reflect their share of total income.

The fund family can charge fees on a different level for each fund in order to take advantage of the positively performing fund. Gaspar et al. found that in the fund family *"high family value" funds (i.e. high fees or high past performers) over perform at the expenses of "low value" funds"*(Gaspar et al., 2006). But this finding is true for not affiliated ones.

Affiliated mutual funds become a provider for insurance against liquidity risk. Bhattacharya, Lee and Pool (2013) discovered that such mutual funds accumulate investment for those family members, which experience temporary liquidity shocks. Nevertheless, the question of interests and favoritism arises again.

Gallaher, Kaniel and Starks (2006) introduced a view on the fund family from a marketing side. They studied the advertising effect on the investors' demand and found that it has a linear relation, independent from the past performance effect.

3 METHOD

Our study is based on a quantitative research that relies on a usage of secondary data from financial databases. We do a purposive sampling – from all Norwegian mutual funds we choose bank mutual fund family, further we eliminate funds within the family that do not have relevant data (by investment style and by historical perspective) (Easterby-Smith, Thorpe, & Jackson, 2012).

In this thesis, we use econometric tools to discover relationships between the mutual funds. Those relationships are based on the correlation between funds in one fund family, and the correlation between funds, which are related to different fund families. Mathematics methods via programming interface are used to solve the optimization problem.

3.1 Approach

All calculations will be made in the R studio software (version 0.99.893), which is a user-friendly interface for work with R (version 3.3.0) (a free software environment for statistical computing and graphics).

Mainly we rely on such packages for R as:

- package *zoo* – S3 Infrastructure for Regular and Irregular Time Series (Z's Ordered Observation) – for storing statistical data on fund;
- package *PerformanceAnalysis* – Econometrics tools for performance and risk analysis – for performance assessment;
- package *fPortfolio* – Rmetrics – Portfolio Selection and Optimization – for performing portfolio analysis.

3.1.1 Returns

We choose to perform our study on a basis of the adjusted NAV. This means, that the share's price of the mutual fund already includes the contribution of additional payments by the mutual funds (i.e. possible dividends, if such appear in a certain period). By doing so, we can omit underestimation of the total returns to the investors, especially when we choose relatively long investing horizons.

Irrespective of data frequency, we calculate returns as continuously compounded ones:

$$r_t = 100\% * \ln\left(\frac{p_t}{p_{t-1}}\right) = 100\ \% * (\ln p_t - \ln p_{t-1}) \tag{3-1}$$

where: r_t denotes compounded returns at the time t, p_t denotes the NAV at the time t, p_{t-1} denotes the NAV of the mutual fund at the previous period for time t, ln denotes the natural logarithm.

We choose this approach due to additivity for obtaining returns for the more aggregated period (for instance, it is possible to find annual returns by the simple addition of each monthly returns). It is worth mentioning, that for finding portfolio returns, where we have weighted assets, such additivity does not work, therefore, it is reasonable to apply weights to absolute value first (Brooks, 2014).

3.1.1.1 Risk-free rate

Since we study the mutual funds with a different country profile, we suggest using two risk-free rates. One for the mutual fund with the internationally oriented portfolio. For such funds, we use 3-month US T-bill rate, but before proceeding the analysis, we have to adjust 3-months T-bill to get a monthly return. We use the next approach:

$$\begin{gathered}(1 + r_{3m}) = (1 + r_m)^3 \\ r_m = \sqrt[3]{1 + r_{3m}} - 1\end{gathered} \tag{3-2}$$

where r_{3m} is US 3 months T-bill interest rate, r_m – estimated monthly return.

3.1.2 Correlation

Financial evaluations often rely on covariance (especially for portfolio risk calculation). It is reasonable, since covariance (3-3) shows an association between two variable (assets in financial perspective).

$$\begin{aligned}cov(X, Y) = \sigma_{XY} &= \frac{1}{n}\sum_{i=1}^{n}(X_i - \bar{X})(Y_i - \bar{Y}) \\ &= \frac{1}{n}((X_1 - \bar{X})(Y_1 - \bar{Y}) + (X_2 - \bar{X})(Y_2 - \bar{Y}) + \cdots + (X_n - \bar{X})(Y_n - \bar{Y}))\end{aligned} \tag{3-3}$$

where $cov(X, Y)\ and\ \sigma_{XY}$ is different ways to denote covariance between variables (assets) X and Y[1], $X_i\ and\ Y_i$ are reference to i^{th} observation/value of variable X and Y respectively, $\bar{X}\ and\ \bar{Y}$ are sample mean value for X and Y respectively.

[1] Dougherty (Dougherty, 2007) suggests to use first notation for sample covariance and second – for population covariance

Formula (3-3) also is useful for variance (σ_X^2) calculation (if we use X variable instead of Y). The variance is a measure of the squared observations' spread relative to their mean. However, finance economy uses square root of the variance – a standard deviation σ_X – as measure of risk: the greater standard deviation, the higher risk of the asset (Spaulding, 2016).

For a descriptive purpose we use correlation as a measure of the strength and usually the direction of this relationship:

$$cor(X,Y) = \frac{\sigma_{XY}}{\sigma_X \sigma_Y} \tag{3-4}$$

3.1.3 Assumption for regression

For performing regression analysis, we will use model B assumptions (Dougherty, 2007):

1) The model has linear relationship between the dependent (Y) and the independent variables (X_i): $Y = \beta_1 + \sum \beta_i X_i + u$;
2) The values of the independent variables are randomly drawn from population;
3) There is no exact linear relationship between the independent variables;
4) The disturbance term u has zero expectation;
5) The disturbance term u is homoscedastic;
6) The values of the disturbance term have independent distributions;
7) The disturbance term and independent variables are distributed independently;
8) The disturbance term has a normal distribution.

3.1.3.1 Multifactor model

For performing better understanding of the influential factor, we will use the multifactor model by Fama and French. For each fund i, based on monthly data for five years, we run next regression (based on least-square approach):

$$R_i - R_f = \gamma_i + \beta_{i1}(R_m - R_f) + \beta_{i2}R_{SMB} + \beta_{i3}R_{HML} + \varepsilon_i \tag{3-5}$$

where R_i is the return of fund i; r_m represents the return of the market portfolio; R_f is a risk free rate; R - the difference between the weighted average yield portfolio of shares of companies with small and large capitalization (small caps over big caps); R_{HML} - the difference between the weighted average yield of portfolio companies with a high and low ratio of book value to market (or value stocks over growth stocks); γ_i is the non-market return, ε_i is a residuals.

As a risk-free rate, we will take T-bill rate since the main part of the mutual fund invest globally.

The market factors affect the return of the mutual funds, but in this study, we are not aimed to define the individual effect of the market parameter on the return. Therefore, we do not make any hypothesis on the direction of factor's influence. Elton, Gruber and Green (2007) suggest, that decomposition of the correlation on systematic and residual parts gives us insight about sources of correlation. We are interested in residual correlation, that could show risk level within the family.

3.1.4 t-test

A t-test is an approach for hypothesis testing that relies on Student t-distribution, that is defined for N independent observation as

$$t \equiv \frac{\bar{x} - \mu}{\frac{s}{\sqrt{N}}} \tag{3-6}$$

where μ is the population mean, $\bar{x}$ is the sample mean, and s is the estimator for population standard deviation (i.e., the sample variance)(Weisstein, n.d.)

This test is useful for comparing a sample mean and a population mean or any other value (more often under "other value" means zero or mean from another sample).

We will use t-test for two purposes:

- to test whether slope coefficient is equal to zero;
- to test whether to mean value is significantly different (for correlation examination).

3.1.4.1 Regression testing

After regression estimation, we need to test, whether a found slope coefficient is significantly different from zero. Therefore, we calculate the practical value of t-test (3-7) and compare it with theoretical, which is available in table form.

$$t_{pr} = \frac{\beta_i}{s.e.(\beta_i)} \tag{3-7}$$

where β_i is estimated slope coefficient for i^{th} independent variable, $s.e.(\beta_i)$ is a standard error of this variable.

If practical value of t-test is greater than corresponding table value, we reject null hypothesis (H0 – Slope is equal to zero)

However, R-Studio tools perform this test automatically, indicating relevant slope coefficient by starring them. Thus, before storing residuals' value, we check slopes and re-run regression after excluding zero-slope independent variable.

3.1.4.2 Two-sample mean testing

The method for comparing two sample means is very similar. The only two differences are the equation used to compute the t-statistic (3-8), and the degrees of freedom (d.o.f.) (3-9) for choosing the tabulate t-value (Stone & Ellis, 2006) . The formulas are given by

$$t_{pr} = \frac{\overline{x_1} - \overline{x_2}}{\sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}} \qquad \textbf{\textit{(3-8)}}$$

$$d.o.f. = \frac{\left(\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}\right)^2}{\frac{s_1^4}{n_1^2(n_1 - 1)} + \frac{s_2^4}{n_2^2(n_2 - 1)}} \qquad \textbf{\textit{(3-9)}}$$

where $\overline{x_1}$ *and* $\overline{x_2}$ are the mean for two sample, n_1 *and* n_2 are the number of observation in each sample, s_1 *and* s_2 are the standard deviation for each sample.

If t-test statistic is greater than the corresponding table value, we reject null hypothesis (H0 – the mean of the two sample is not the different).

Nevertheless, we do not need to calculate the t-test by these formulas – we use a function *t.test()* in RStudio. This function requires inserting two data series and specifying whether two sample have equal variances. That is why before proceeding with t-test we are doing Fisher's F-test to verify the homoscedasticity. The function *var.test()* in RStudio does it. If we obtain p-value (as part of the function's output) greater than 0.05, then we can assume that the two variances are homogeneous (H0 – the variance of two sample are homogeneous) (Crawley, 2014: 88).

3.1.5 Optimization process

Addressing the portfolio optimization problem, we have to set a few assumptions about the investor preferences and strategy:

- Considering the risk-free asset and maximizing Sharpe's ratio (finding the tangency portfolio) – the investor can choose the desired risk level by choosing a point on the capital allocation line, where the slope of the efficient frontier equals the capital allocation line. In this study, we assume that the investor puts money only in risk portfolio – i.e. there is no risk-free borrowing or lending. In this way, the investor is neither too much risk averse to invest mostly in risk-free (T-bill), nor too risky for borrowing at risk-free to invest more in the risky portfolio (according to mutual fund separation theorem)(Zivot, 2013).
- The investor could invest only in the stock or/and bond – there is no investment in the money market.
- There is no short sale – all portfolio's assets have weight $0\% \leq w_{asset} \leq 100\%$.
- The investor chooses between efficient portfolios – the portfolios that offer the greatest return for a certain risk (Harvey & Gray, 1997).
- All tangency portfolios are associated with different risk; therefore, it is reasonable to compare their performance with the market by Sharpe ratio. However, solely, Sharpe ratio does not always effectively represent competition between portfolios. Therefore, in addition to it, we use Modigliani risk-adjusted performance, that enables comparing portfolios by excess return on the benchmark risk level. As a benchmark we choose OSEBX.

3.1.5.1 Tangency portfolio

All portfolios, that we create, are tangency portfolios i.e. they maximize Sharpe ratio. Therefore, we have maximization problem, that in general for n assets looks like (3-10):

$$\begin{aligned} &\max_{w_i} SR_p = \frac{R_p - R_f}{\sigma_p} \quad s.t. \\ &R_p = \sum_{i=1}^{n} w_i R_i = W'R, \\ &\sigma_p^2 = \mathrm{W}'\Sigma\, W, \\ &\sum_{i=1}^{n} w_i = 1 \end{aligned} \qquad \textbf{\textit{(3-10)}}$$

where w_i denotes weight of the fund i in the portfolio, W is a vector of all weights, W´ is transposed weight's matrix, R is a vector of all fund expected return R_i, $\sum$ denotes covariance matrix between all n funds. For two assets portfolio, this problem is solved too (Zivot, 2013):

$$\begin{aligned} &w_1 = \frac{(R_1 - R_f)\sigma_2^2 - (R_2 - R_f)\sigma_{12}}{(R_1 - R_f)\sigma_2^2 + (R_2 - R_f)\sigma_1^2 - (R_1 - R_f + R_2 - R_f)\sigma_{12}}, \\ &w_2 = 1 - w_1 \end{aligned} \qquad \textbf{\textit{(3-11)}}$$

However, such calculation is not applicable to short-sale elimination. Thus to perform computation, we use the *tangencyPortfolio()* function from R-package *fPortfolio*, setting its specification for match our assumptions. We set a risk-free rate equal to average T-bill return. This function works with full family's portfolio as well as two assets one.

3.1.5.2 Portfolio frontier

The *portfolioFrontier()* function is supporting, that is used for the plot creation. Before its application, we make specifications for it. The most of the parameters remain as in the *tangencyPortfolio*() specification, by we set the specification *setNFrontierPoints* equal to 15. This mean that the program will calculate 15 portfolios which lay on efficient portfolio line with an equal step between the return of those portfolios. We are interested in upper part of the line.

3.2 Data collection

The data upon the mutual funds' performance was gathered from the TITLON project. Our target was to use all mutual fund for the mentioned fund family (DNB Asset Management and ODIN) during five years – from 2011 to 2015. There were 65 mutual funds in ODIN listed on TITLON and 192 funds within DNB family. But that amount contained a duplication of each fund (after the funds' name changing or their merging), that reduced the sample significantly. Additionally, we eliminated from the sample old funds (which did not perform until 2015) and relatively new funds (that were established after 2011). After mentioned selection we got access to the daily data for **24** mutual funds, owned by DNB and 16 mutual funds, owned by ODIN.

Information about the mutual funds' structure by fee, risk, country and stocks profile is available on the official website of DNB (https://www.dnb.no/). Additionally, we have examined annual report (unfortunately, there is only the last year report in open access). Historical data for ODIN fund family was accessed via TITLON, additional qualitative information is gathered at the official website (http://odinfond.no/).

3.3 Limitations

The study depends on monthly data on two fund family, defined by the last date of the month. We suggest, that result could be different for another return calculation. The study is based on the realized data, and could not be used for performance forecast. The obtained results are not inductively applicable for other fund families.

4 PRACTICAL MUTUAL FUND FUNCTIONING

Mutual funds and securities funds are not a newly introduces investment tools for Scandinavia in general and Norway in particular. Starting with the opening of the first ever Norwegian mutual fund in 1981, interest in the investment mechanisms it provides keeps growing every year. The practice of mutual funds using in Scandinavia markets has proven worldwide tendency of higher long-term expected return conjugated with higher risks in the sense that investors/clients can secure a significant part of their savings. Let's address Finanstilsynet, as a financial supervisory authority in Norway, to classify and identify what is considered to be a mutual fund. The Act on securities fund defines mutual fund as:

"*An independent pool of assets which has arisen through capital contributions from an undefined range of persons against the issuance of units in the fund and which consists essentially of financial instruments and/or deposits in a credit institution.*"(Finanstilsynet, 2012)

The explanation is in general no different to such given in Europe at the beginning of mutual funds regulation establishment, but so are the people motives to use the mutual fund in Norway – personal management, affordability, diversification, flexibility, liquidity.

Central bureau of statistics in Norway (Statistisk sentralbyrå, 2015) demonstrates tendencies in usage and popularity throughout mutual funds variety represented to Norwegian market (Figure 1).

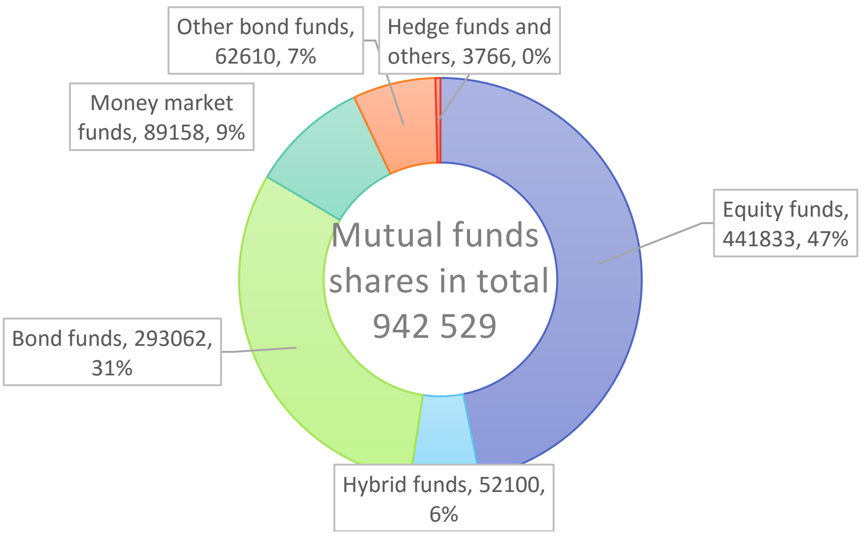

Figure 1. Stocks of mutual funds shares by type as of 30th September 2015 (Market value in NOK Billion)

We can see how heavily equity, bond and money market funds are dominating in shares over other types of mutual funds by 30-th September of 2015. We will also demonstrate how such tendency is reflected in banks mutual fund portfolio in 4.1-4.3. It is already seen, that even though the risk is significantly higher upon investing in stocks and equity funds, higher expected return that is following such funds attracts Norwegian investors in the considerably bigger deal. That can be related to historical tendencies of mutual fund functioning in Norway , that has proven that alike most worldwide practice, Norwegian mutual funds (that are index mutual funds) mostly beat the market, represented by Oslo Børs (Hornenes et al., 2015).

DNB and ODIN fund families are the biggest on the Norwegian market with respect to individual investors. Based on the market statistics from Verdipapirfondenes Forening for 2015, DNB has 28.93% on the market and ODIN has 15.32% (their closest competitor's – SKAGEN – market share is 13.65%). While DNB has a leading position on mutual fund market in general (individual and institutional investors) – 24.20%, ODIN obtains only 4.53%, since it does not develop a wide range of opportunities for institutional investors (Verdipapirfondenes forening, 2016).

4.1 DNB family of mutual fund

DNB as one of Norwegian largest banks has already introduced a variety of portfolios to their clients. DNB Asset Management company is a subsidiary of DNB, that is responsible for mutual fund management. There are 92 funds in DNB possession, 91 of them are suitable for institutional investors, 83 funds are oriented on individual investors. However, only 15 funds were available for an average client of the bank via web-site in 2015.

DNB promotes its combination funds more than others. They are called Aktiv10, Aktiv30, Aktiv50, Aktiv80 and Aktiv100. The number in the names identifies stock weight in the mutual funds. All mentioned mutual funds meet the UCITS[2] requirements.

These mutual funds have the same level of minimum investing amount – it is just 100 NOK. Also, they have no loads during buy-sell operation – there is no fee to proceed purchase or redemption. But investing in these fund implies the payment of annual fee – managerial honorary (forvalterhonorar in Norwegian), which differ from fund to fund.

[2] UCITS - Undertakings for Collective Investment in Transferable Securities – is an institutional regulatory legislation, that defines order of the mutual funds' activity in European Union

The mutual funds of Aktiv-type are index based. This means that mutual fund tends to *"achieve the same return as a particular market index"* (U.S. Securities and Exchange Commission, 2010, p. 11). For the benchmark, Aktiv mutual funds use synthetic index, based on weighted values of the next indices:

- Bond indices:
  - ST1X - Government Bond Index, fix modified duration of 0.25 years;
  - ST4X - Government Bond Index, fix modified duration of 3 years;
  - Barclays Global Agg Corp Bond Index;
- Stock indices:
  - OSEFX – Oslo Børs Mutual Fund index;
  - MSCI World All Country Index.

However, the weight of each index is different for each mutual funds in order to reflect proportion between stocks and bonds holdings. But it is worth mentioning, that mutual funds value also consists of other instruments (Figure 2).

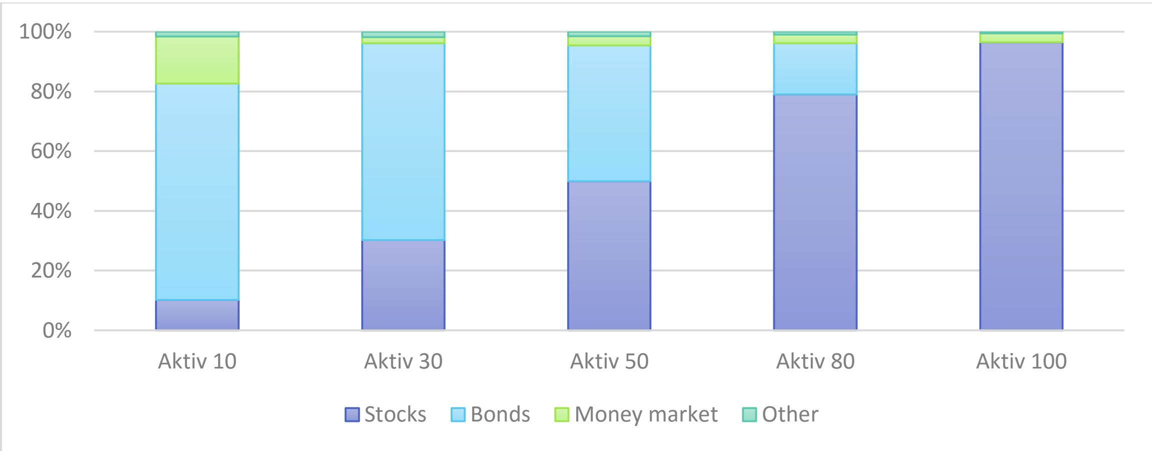

Figure 2. Structure of the mutual funds' investment by instruments (2016)

Another feature of the Aktiv mutual funds is that mainly their holding consists of other DNB mutual fund. This means Aktiv funds invest mostly within the family and to some extension could be categorized as affiliated ones.

Aktiv10 is the oldest fund among "Aktiv"-type. It is launched in 1995. It is identified as international combination fund. Due to a small share of the stocks, the annual fee is low – 0.6%. Top ten investments hold 92.73% of the portfolio (according to data on 31.01.2016) and include only DNB family funds.

Aktiv30 offers to invest 30% in stocks. It is established in 2010 and it is the youngest fund among Aktiv-type. Aktiv30 is identified as international combination fund. Due to a relatively small share of the stocks, the annual fee is low – 1%. Top ten investments hold 82.04% of the portfolio (according to data on 31.01.2016) and include only DNB family funds.

Aktiv50 offers to invest equally in stocks and bonds. It is established in 1997 and is identified as international combination fund. The annual fee is low – 1.2%. Top ten investments hold 77% of the portfolio (according to data on 31.01.2016) and include except DNB family funds also Consumer Discretionary Select Sector ETF (USA), Topix Index Future Mar 16 / TPH6.

Aktiv80 offers to invest 80% in stocks. It is established in 2005 and is identified as international combination fund. Due to increased part of the stocks, the annual fee is higher – 1.3%. Top ten investments hold 75.5% of the portfolio (according to data on 31.01.2016) and include except DNB family funds also Consumer Discretionary Select Sector ETF (USA), Topix Index Future Mar 16 / TPH6 and Financial Select Sector SPDR ETF (USA).

Aktiv100 offers to invest fully in stocks. It is established in 2005 and is identified as international combination fund. Due to the stocks holdings, the annual fee is the highest – 1.4%. Top ten investments hold 76.93% of the portfolio (according to data on 31.01.2016) and include except DNB family funds also Consumer Discretionary Select Sector ETF (USA), Topix Index Future Mar 16 / TPH6, Financial Select Sector SPDR ETF (USA) and Dow Jones STOXX 600 Oil & GasEX ETF (Germany).

Analysis of the country structure of this type of DNB funds (we consider top 10 countries for each of the funds) shows, that 45-50% of the mutual holding are US stocks and bond while in Norwegian assets they invest almost twice less – only 12-14% (Figure 3).

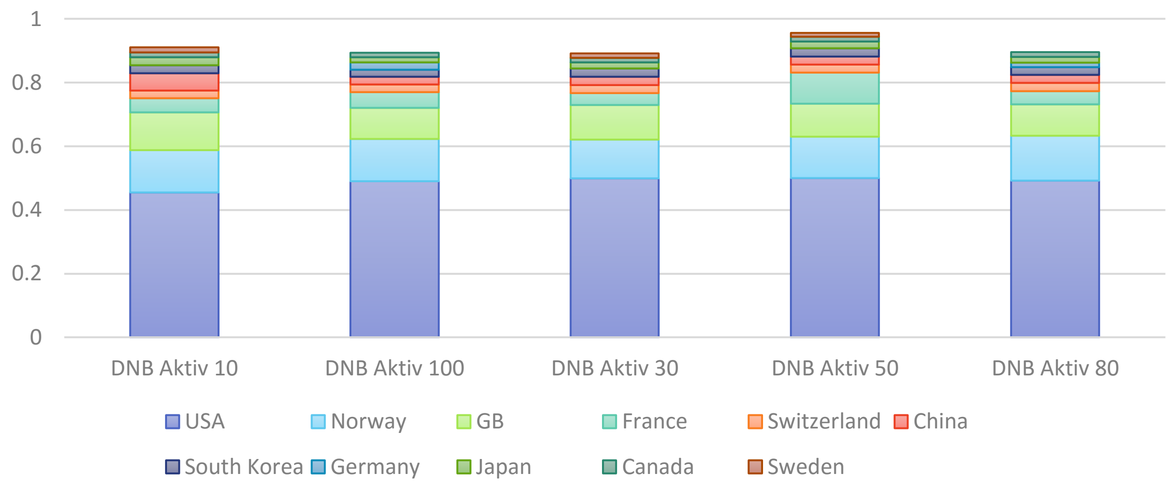

Figure 3. Country profile of the "Aktiv" mutual funds of DNB (2015)

Since there are just 15 funds at a website available for analysis, we use only that data – data on DNB Global, DNB Global Emerging Markets, DNB Global Indeks, DNB Miljøinvest, DNB Navigator, DNB Norden, DNB Nordic Technology, DNB Norge, DNB Norge Indeks, DNB SMB.

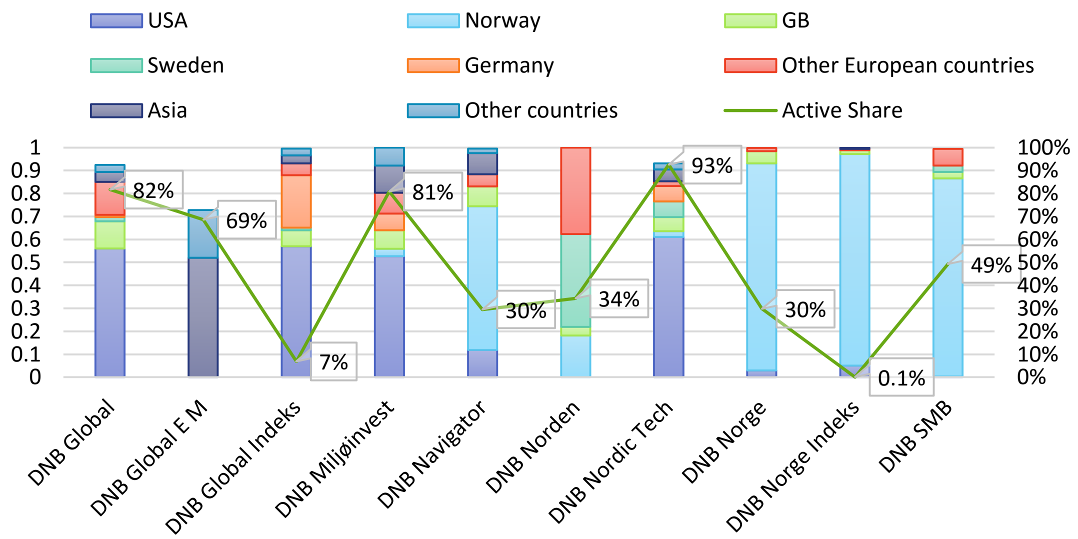

Figure 4. Countries structure of the DNB stock funds

DNB Norge Indeks and DNB Global Indeks, which have the lowest active share, have an annual fee of 0.3%, other funds set fee level within 1.3-1.8%.

4.2 ODIN family of mutual fund

ODIN fund management is a team of Norwegian mutual fund management specialists that is established in Oslo in 1990 and is a subsidiary of Sparebank1. The company provides clients with access to 52 different types of portfolios within different countries (mostly Scandinavian), markets or company type included in the portfolio. 38 portfolios are accessible for regular clients while institutional investors could consider 51 funds(Verdipapirfondenes forening, 2016).

In variety of service range, they are able to provide to their clients, there is a few especially valuable and worth mentioning

- Investment possibility into broad range of diversified portfolio
- Automatic and free of charge account establishment in Norwegian Central Securities Depository (VPS) upon subscription.
- Consultations along investment considering valuable decisions and specifics of best buy/sell timing
- Free of charge in-between funds transfers

Worth mentioning time-based reports and recommendations upon market situations considering portfolios provided by the company. Its content reveals information upon return of equity funds, profit for the year and their appropriation as well as notes and/or valuable information from the board of directors meeting.

Personal data asset sheet reveals information upon each portfolio proposed by company services personally. It usually concentrates on portfolio return, key figures, financial statements, balance sheet, shareholder’s equity, portfolio composition, and risk measurement. Information is suggested in the easy and readable way and is followed by comments and explanations given by managers responsible for this portfolio, its allocation, and efficiency.

ODIN fund is using the reader-friendly style of a report providing a good balance of key data. They are revealing benchmark ratios, risk measurement, volatility and NAV ratios for those clients that are interested in economic analysis as well as explanation and follow-ups for most of those indicators for clients who are just making first steps in mutual fund investing.

4.2.1 Combination funds

ODIN has three combination mutual funds, that are defined as international oriented. The combination funds’ value is 27,33% of total ODIN assets value. All of them are established in 2009. Comparing to DNB funds, ODIN combination funds do not match UTICS requirements.

All ODIN combination funds share the same county structure of investment (Figure 5) as well as the industry breakdown.

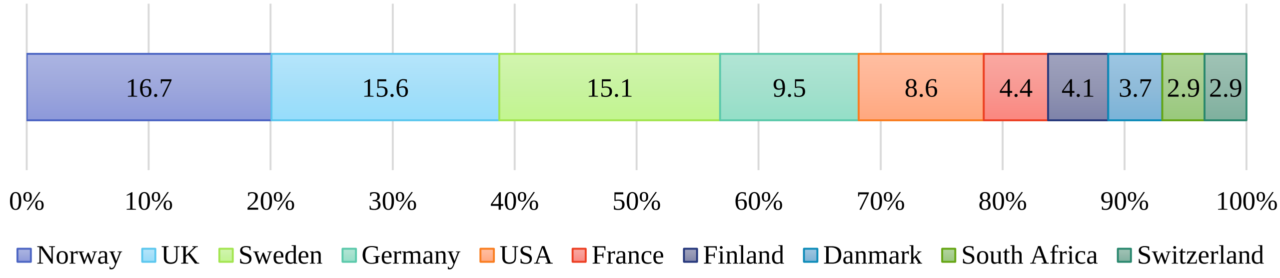

Figure 5. Country structure of investment by ODIN combination funds (2015)

ODIN Horisont invests 75% of the portfolio in stocks and 25% in bonds. As tracking index, ODIN Horisont uses a synthetic index with Oslo Børs Statsobligasjonsindeks 1 år (ST3X) 25%, MSCI World Net Index 37,5%, VINX Benchmark Cap NOK NI 37,5%. The annual fee is 1.25%.

ODIN Flex invests equally in stocks and bonds. As tracking index, ODIN Horisont uses a synthetic index with Oslo Børs Statsobligasjonsindeks 1 år (ST3X) 50%, MSCI World Net Index 25%, VINX Benchmark Cap NOK NI 25%. The annual fee is 1%.

ODIN Konservativ invests 25% of the portfolio in stocks and 75% in bonds. As tracking index, ODIN Horisont uses a synthetic index with Oslo Børs Statsobligasjonsindeks 1 år (ST3X) 75%, MSCI World Net Index 12.5%, VINX Benchmark Cap NOK NI 12.5%. The annual fee is 0.7%. But it has a front and end-load fee of 2.5% and 0.5%.

5 FINDINGS

5.1 Descriptive statistics

We divide all mutual funds within the family into three types – stock mutual fund, bond mutual fund and combination mutual funds (the last ones invest into a mixture of stock and bond) (Appendix A) . For each individual, we calculate the monthly return and the standard deviation for each individual fund (Data table 2 and Data table 3 in Appendix B). For further analysis, we provide calculation also for the market indices – OsloBørs Aksje indeks (OSEAX), OsloBørs Hovedindeks (OSEBX) and 3 months "Statsobligasjonsindeks" (ST1X) in the same way (Data table 4 in Appendix B). Then we aggregated statistics by type of the mutual funds. As shown in Table 5-1, both fund families earn almost the same return but assuming Sharpe ratio, DNB funds perform better than the funds in ODIN family. It is worth mentioning, that calculated average returns are not adjusted to the risk-free rate.

Table 5-1. Average monthly return and risk by type of the mutual fund (whole period)

	No of funds	Average return	Average risk	Sharpe ratio
DNB family:				
- Combination	5	0.64%	1.80%	0.3759
- Stock	15	0.70%	3.76%	0.2347
- Bond	3	0.38%	0.42%	0.7745
ODIN family:				
- Combination	3	0.55%	1.79%	0.2930
- Stock	12	0.72%	4.10%	0.1702
- Bond	3	0.34%	0.55%	0.6583
Market				
- OSEAX		0.52%	0.15%	0.1222
- OSEBX		0.60%	0.15%	0.1407
- ST1X		0.24%	0.02%	0.1339

The average return for market indices is positive and much less volatile. But the average monthly return for the market is lower. The assessment, based on Sharpe ratio, shows that the mutual funds families overperform market, moreover they earn a higher level of the returns.

5.1.1 Correlation within and between fund families

For further analysis, we calculate the correlation between each pair of the fund. For this, in the DNB (ODIN) fund family, we compute correlation for each DNB (ODIN) fund with every fund of the same type and of the different one (Data table 5 and Data table 6 in Appendix C). Also, we define the correlation between fund from the different families, for instance, the correlation between each ODIN combination mutual fund with each DNB stock mutual fund

(Data table 7 in Appendix C). Therefore, we average results across both families by type of the mutual funds. We calculate statistical significance by t-test of difference in mean correlation after performing a test of variance equality.

Based on obtained results (presented in Table 5-2), there is a tendency for the increased correlation within the family, compared to outside correlation for the most pairs of types. For example, the correlation between combination and stock mutual fund within the family in average is 0.7304, while the correlation between the same pair of families is 0.6849. The opposite relationship is observed only for the stock-bond pairing: on average stock and bond mutual fund from different families is correlated more, than whether they are from the same family (correlation outside is equal to 0.2759, while within family 0.0951).

Table 5-2. Return correlation by the type of the mutual fund within and between fund family

	Within family	***Between family***	***t-Stat***	***p-Value***
Combination-combination	91.72%	79.52%	4.3614	0.0008
Stock-stock	60.57%	64.33%	-1.8057	0.0721
Bond-bond	69.73%	56.24%	0.8289	0.4278
Combination-stock	73.05%	68.49%	2.1764	0.0307
Combination-bond	18.25%	6.74%	1.9921	0.0519
Stock-bond	9.51%	27.59%	-3.9744	0.0001

Comparing all pair of the funds' types, the average return within and outside the family is significantly different. The bond mutual funds have a weaker influence on the fund families. According to the t-test, the difference of the return's correlation for combination-combination and combination-stock are significantly higher within the family at the 5% level. The stock-bond return correlation is significantly higher for the fund from different families at the 1% level. The only correlation between pairing stock-stock and bond-bond mutual funds' return could not be treated as significantly different; the pairing of combination and bond gets borderline value for acceptance/ rejection of the hypothesis. However, if we shift significance level to 10%, the difference in stock-stock and combination-bond pairing will be significant.

Since we have found that correlations within and between fund families are significantly different, it is reasonable to examine what causes such difference.

5.1.1.1 Residuals effect on correlation

We estimated regression (3-5) and extracted residuals for each mutual fund. Since all mentioned funds are Norwegian, but almost 50% they invest in US securities, we decided to T-bill as the risk-free rate. Afterwards, we computed all mentioned above correlations (within the family and between families) for residuals (45Appendix D).

We summarized results in Table 5-3 only for those pair of the mutual funds, that appear to have significant correlation on previous tests at 5% significance (including pairing with a borderline difference).

Table 5-3. Determinants of the differences in fund correlations within and between families

	Return correlation difference	***Systematic component difference***	***Idiosyncratic component difference***	***Ratio (3)/(1)***
	1	*2*	*3*	*4*
Combination-combination	0.122	0.000	0.122	1.000
Combination-stock	0.046	0.003	0.048	1.060
Combination-bond	0.115	-0.008	0.107	0.931
Stock-bond	-0.181	0.142	-0.039	0.217

Column 1 of Table 5-3 shows the differences in correlation found during examination correlation in general (Table 5-2). Column 3 shows the difference in correlation that is caused by the residual. The control for a ratio of these two columns (the result is presented in column 4) reveals that higher correlation within the family is led by higher residuals' correlation. The residuals part of the correlation makes around 100% of total one for such pairs as combination-combination, combination-stock and combination bond. For example, for combination-bond the overall percentage difference in correlation due to the residuals' correlation is 93.1%. For stock-bond pairing correlation, residuals' correlation is not so influential – it does not exceed 21.7%. It is noteworthy, that for stock-bond correlation, that is significantly higher between families, 98% of correlation is connected to market factors.

This result shows, that correlation between funds within the family is higher only for those pairings, which include combination funds. It means, that management decision (that is assumed to be residual in this model) influence relationships between fund in ownership. It makes sense since fund family is used to investing in own mutual fund. Such investment style of the family could affect the total risk of the individual investor since diversification of the combination funds is significantly relies on diversification of other portfolios (funds) in possession.

5.2 Portfolio analysis

We have started with calculating of Modigliani risk-adjusted measure in order to compare how the funds perform, compared to the market. We define OSEBX as the market and T-bill rate as risk-free. For computing values of both indicators, we use functions inside the package *PerformanceAnalysis* – a *Modigliani()* and a *SharpeRatio()*. Obtained results[3] are presented in Data table 2 (for DNB) and Data table 3 (for ODIN) in Appendix B.

Since two performance measures have the common base for the calculation – Sharpe ratio – they rank the mutual fund in the same way. The best performers are the bond mutual funds in both families, but among the stock funds, DNB family does it better, than ODIN. Three stock after bond funds in each family are DNB Healthcare, DNB USA and DNB Global IV; ODIN Global II, ODIN Global II, and ODIN Europe II. However, DNB family by these fund overperform OSEBX by 1-1.6%, while ODIN only by 0.5-0.7%. The similar tendency presents also for the combination mutual funds: the fund with a greater part of the bonds has higher Sharpe /M2 ratio.

5.2.1 Tangency portfolio of two mutual funds

We calculate all possible tangency portfolio for DNB (Data table 11 in Appendix E) and ODIN (Data table 12 in Appendix E), combining each family's stock fund with each bond one. Therefore, we get 45 tangency portfolios within DNB family and 30 tangency portfolio within ODIN family. Also, we create 75 mixed portfolios: they include all pairing of DNB's stock and ODIN bond funds as well as the pairing of DNB's bond and ODIN stock funds (Data table 13 in Appendix E).

For the portfolios with only DNB family funds, three portfolios suggest investment in bond less than 50%, one suggests investing 100% in bonds; the other 43 portfolios vary bond share between 90% and 100%. All artificial portfolios have Sharpe ratio higher than existing combination funds as well as the market.

For the portfolios with only ODIN family funds, two portfolios suggest investment in bond less than 90%, nine suggest investing 100% in bonds; the other 19 portfolios vary bond

[3] In the mentioned tables 1 – is the worth performed fund

share between 90% and 100%. There are two tangency portfolios for ODIN fund, that have lower Sharpe ratio than DNB Aktiv 10 and Aktiv 30 (but they beat other combination funds).

For the portfolios with mixed family funds, two portfolios suggest investment in bond less than 35% (Sharpe ratio 0.75), five suggests investing 60-80% in bonds (Sharpe ratios are different, from 0.43 to 0.96); 19 portfolios have 100% of bond; the other 53 portfolios vary bond share between 90% and 100%. Most artificial portfolios have Sharpe ratio higher than existing combination funds as well as the market, but 14 of them have lower Sharpe ratio than DNB Aktiv 10 and Aktiv 30 (but they beat other combination funds and the market index).

We choose the preferred portfolio following the comparison by M2 measure, which defines better portfolio by the highest level of return, given risk equal to the market index (OSEBX) (Table 5-4).

Table 5-4. Comparison of the portfolios – the combination funds against tangency portfolio (two assets)

	Stock weight	***Bond weight***	***Expected return***	***Average risk***	***Sharpe***	***M2***
From DNB №22	5.86%	94.14%	0.50%	0.48%	0.9329	3.69%
From ODIN №22	2.26%	97.74%	0.32%	0.26%	1.0071	3.98%
Mixed №22	3.59%	96.41%	0.36%	0.30%	1.0225	4.04%
DNB Aktiv 10	10.00%	90.00%	0.34%	0.50%	0.5661	2.26%
DNB Aktiv 30	30.00%	70.00%	0.48%	1.04%	0.4074	1.64%
DNB Aktiv 50	50.00%	50.00%	0.61%	1.70%	0.3283	1.33%
DNB Aktiv 80	80.00%	20.00%	0.81%	2.52%	0.3022	1.23%
DNB Aktiv 100	100.00%	0.00%	0.95%	3.26%	0.2754	1.13%
ODIN Konservativ	25.00%	75.00%	0.43%	1.08%	0.3521	1.43%
ODIN Flex	50.00%	50.00%	0.56%	1.74%	0.2934	1.20%

Left side column defines portfolios: *From DNB №22* shows that it is 22nd portfolio (in Appendix E), created of DNB Healthcare (stock) and DNB Kredittobligasjon (bond); portfolio *From ODIN №22* invests in ODIN Norden II (stock) and ODIN Obligasjon (bond); portfolio *Mixed № 22* includes assets from DNB Healthcare and ODIN Obligasjon.

Table 5-4 shows, that the artificial portfolios offer greater Sharpe ratio. In the same time, mixed artificial portfolio, with stocks from DNB and bonds from ODIN perform better than the other. The mixed portfolios earn 4.04% monthly – twice more, than the best performer from existing funds.

However, this analysis is based on tangency portfolio, created just with two assets, that is non-realistic since banks include a greater amount of the funds into portfolio (but in average 80-90% of the fund's value comes from top-10 assets. Thus, we want also investigate more diversified artificial portfolios.

5.2.2 Efficient Frontier

Using only stock and bond mutual funds from each fund family, we define an efficient portfolio for each family, which [portfolio] theoretically can include any amount of the assets - from 2 to 18 for DNB fund family, from 2 to 13 – for ODIN family.

Using the *portfolioFrontier()* function we got the sets of efficient portfolios – the combination of the mutual funds, that give us the highest possible return for each risk value. With the *tangencyPortfolio()* function we find the portfolio with maximum Sharpe ratio. The plot on Figure 6 represented the efficient frontiers of DNB (Appendix F) with respect to expected return and risk.

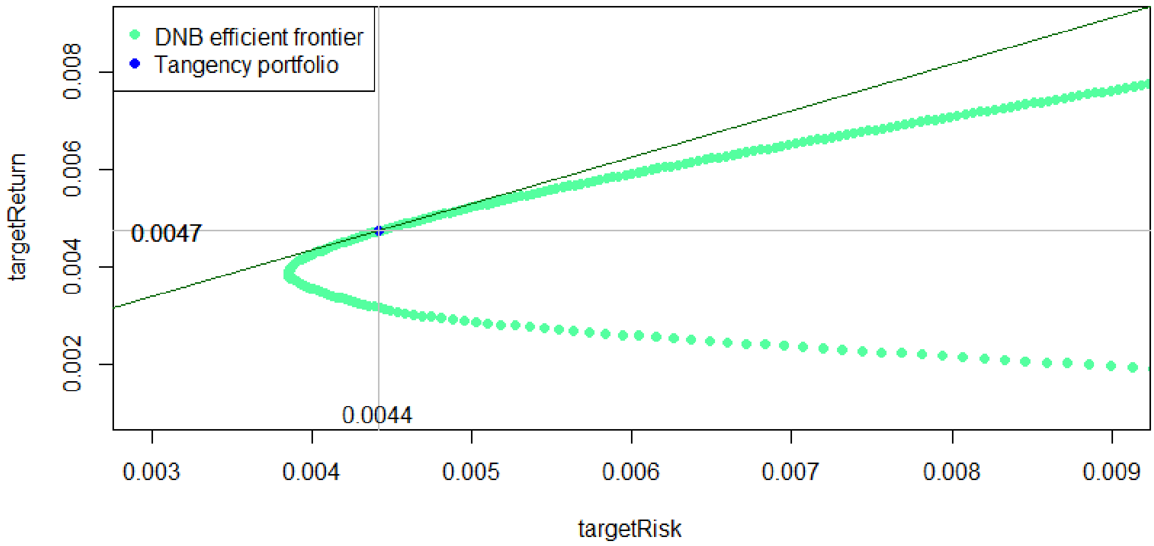

Figure 6. Efficient frontier for DNB fund family (excluding the combination funds)

The defined tangency portfolio (Appendix I) suggests investments in five assets: DNB Norge Selektiv, DNB USA, DNB Healthcare, DNB SMB, and DNB Kredittobligasjon in proportion 93.6% : 6.4% of the bond and the stock. This portfolio has Sharpe ratio equal to 0.95016.

The plot on Figure 7 represented all non-combination funds of ODIN with respect to expected return and risk. ODIN efficient frontier points are calculated by the function *portfolioFrontier()* and presented in (Appendix G).

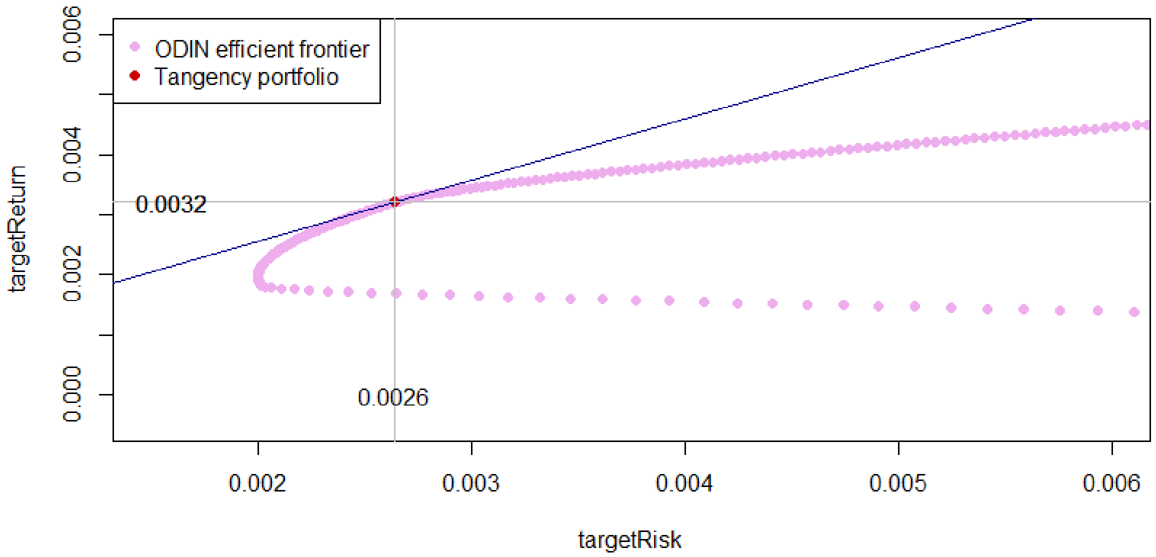

Figure 7. Efficient frontier for ODIN fund family (excluding the combination funds)

The defined tangency portfolio (Appendix I) suggests investments in two assets: ODIN Norden II and ODIN Obligasjon 97.7% : 2.3%. This portfolio has Sharpe ratio equal to 1.0156.

We define the efficient frontier for the mixture of the funds (Appendix H). Also, we calculate tangency portfolio for them (Figure 8) (data available in Appendix I).

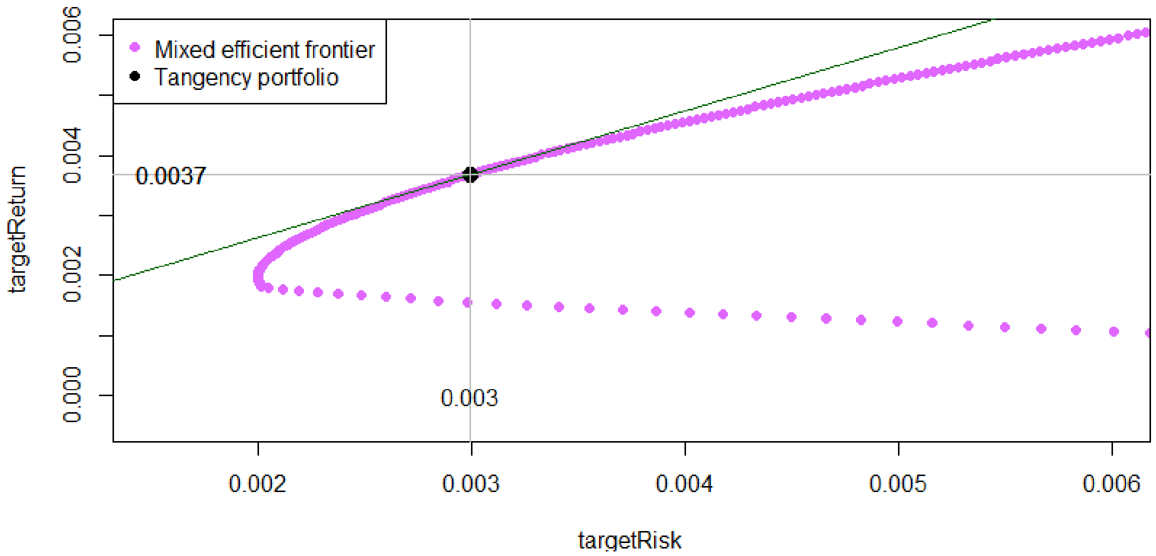

Figure 8. Efficient frontier for the fund families (excluding the combination funds)

The defined tangency portfolio suggests investments in four assets: ODIN Norden II, ODIN Obligasjon and DNB Healthcare, DNB Kredittobligasjon in proportion 3.9% : 96.1% of the stock and the bond. This portfolio has Sharpe ratio equal to 1.0518.

Table 5-5 summarize the results from this section. As we see, all tangency portfolio, created with the non-restricted entry number of the assets (we got a portfolio with four, three and seven assets in them) could perform better, than the combination fund, based on a Sharpe ratio. Newly created portfolios over perform by more than twice (3.76%- 4.15% compared to 1.16%-2.62% of the combination funds) at given market risk.

Table 5-5. Comparison of the portfolios – the combination funds against tangency portfolio (unrestricted number of assets)

	Stocks	*Bonds*	*Mu2*	*Sigma3*	*Sharpe*	*M2*
Mixed	3.95%	96.05%	0.37%	0.30%	1.05184	4.15%
From ODIN	2.29%	97.71%	0.32%	0.26%	1.01557	4.01%
From DNB	6.38%	93.62%	0.47%	0.44%	0.95016	3.76%
DNB Aktov 10	10.00%	90.00%	0.34%	0.50%	0.5661	2.26%
DNB Aktiv 30	30.00%	70.00%	0.48%	1.04%	0.4074	1.64%
DNB Aktiv 50	50.00%	50.00%	0.61%	1.70%	0.3283	1.33%
DNB Aktiv 80	80.00%	20.00%	0.81%	2.52%	0.3022	1.23%
DNB Aktiv 100	100.00%	0.00%	0.95%	3.26%	0.2754	1.13%
ODIN Konservativ	25.00%	75.00%	0.43%	1.08%	0.3521	1.43%
ODIN Flex	50.00%	50.00%	0.56%	1.74%	0.2934	1.20%
ODIN Horisont	75.00%	25.00%	0.65%	2.55%	0.2334	0.96%

However, this analysis is based on a historical data, which could not be a source for reliable assessment of the future fund performance. An existence of the better artificial portfolio could be a reason for questioning mutual family management efficiency during analyzed period. While we do not have relevant information about portfolio creation in mentioned family, we remain satisfied with such results.

6 SUMMARY

The DNB and ODIN fund families own a range of different mutual funds, which meet different investment style's requirements of the clients. While market share indicates relative success on the market within individual investors (DNB is the first (28.93% of the market), followed by ODIN (with 15.32%), the question about a quality of the performance arises.

Preliminary ex-post analysis proves, that both families overperform OSEAX, ST1X and OSEBX (which stand for stock, bond and broad market indices) by each fund's category (stock, bond and combination funds). The dramatic difference in Sharpe ratio appears between the bond indices and bond mutual funds (0.1339 and 0.65-0.77 respectively). Funds' average monthly returns by category look comparable (combination 0.55-0.64%, stock 0.72-0.7%, and bond 0.34-0.38% for ODIN and DNB respectively) as well as risk variance pattern.

However, the difference in return exists, so we have tested whether it is significant. Findings suggest, that the correlation between combination-combination, combination-stock, and combination-bond pairings is significantly higher within families while the correlation between stocks and bonds funds is significantly higher between families. Using multiple regressions (by Fama-French model), we investigate, what is the reason for higher correlation to occur. The residuals difference's influence accounts for around 100% of total return difference. This means, that market factors are not decisive for pairing like combination-combination, combination-stock, combination-bond. It makes sense since the family is used to invest in own funds – therefore, DNB/ ODIN combination funds invest in DNB/ODIN stock/bond funds, what makes them higher correlated. Only for stock-bond pairing the market (in general) affects return on 78.3% .

The optimization process aims to define efficient artificial portfolios (that offer higher Sharpe ratio, comparing with existing combination funds), created by mixing two assets at first, then consider full family opportunities. All artificial portfolios have higher Sharpe ratio, but the ratio is not exhaustive criteria for referencing. Modigliani risk-adjusted performance measures, which return will have a portfolio with risk equal to the market. We refer to OSEBX index as the market.

All artificial portfolios overperform existing combination funds of families by Sharpe ratio. Six artificial portfolios, chosen with the highest ratio (three for each approach – two and any amount of assets) suggest investing 93.6%-97.7% in bonds. Mixed portfolios – that combine DNB and ODIN funds – earn more than 4% of the return by M2. This is twice greater than DNB Aktiv 10 offers (it is a fund with greatest M2 within existing combination funds).

Findings suggest, that there is a possibility to create better portfolios within the family. Thus, based on the realized returns, fund family could consider the opportunity to launch another category of the combination fund, that would reflect 0.05 : 0.95 stock-bond structure. From the investor's point of view, it is advantageous to put money in different families – average correlation between funds from different families is significantly lower. In such way, the investor would reduce risk and obtain higher Sharpe ratio portfolio.

Since a mutual fund family performance is not studied in-depth, there are a lot of problems to address within further research. For instance, it will be a valuable study on a strategy, that uses a broad stock index combined with a bond index in order to reveal whether "synthetic" market index performs better than the bank funds. We assume that in the context of costs, it would be cheaper to prefer index portfolios over bank funds, but a deeper research may find out whether the returns would be better as well. Furthermore, it is of a special interest to investigate other sources of correlation differences, such as common holdings, variance differences and their influence on the returns.

7 LITERATURE LIST

Armstrong, F. (2013). Fama-French Three Factor Model.

Barras, L., Scaillet, O., & Wermers, R. (2010). False Discoveries in Mutual Fund Performance: Measuring Luck in Estimated Alphas. *The Journal of Finance*, *65*, 179–216.

Bhattacharya, U., Lee, J. H., & Pool, V. K. (2013). Conflicting Family Values in Mutual Fund Families. *Journal of Finance*, *68*, 173–200.

Bollen, N., & Busse, J. (2005). Short-Term Persistence in Mutual Fund Performance. *The Review of Financial Study*, *18*, 569–597.

Bond Pricing: An Educated Guess. (2004). *Capital Management Group, LLC*, p. 2.

Brooks, C. (2014). *Introductory Econometrics for Finance*. Cambridge University Press. Retrieved from https://books.google.com/books?id=qTE4AwAAQBAJ&pgis=1

Brustad, J. M., & Aksjer, K. (2013). *Avkastning og risiko for norske aksjefond : Har størrelse noen betydning ?* Universitetet for miljø- biovitenskap.

Carhart, M. (1997). On Persistence in Mutual Fund Performance. *The Journal of Finance*, *52*, 57–82.

Casabona, P., & Traficanti, R. M. (2002). *Investment Pricing Methods: A Guide for Accounting and Financial Professionals*. John Wiley & Sons. Retrieved from https://books.google.com/books?id=J_djwZdk9tcC&pgis=1

Chevalier, J., & Ellison, G. (1997). Risk-Taking By Mutual Funds as a Response to Incentives. *Journal of Political Economy*, *105*, 1167–1200.

Choong, P., & Richardson, P. (2014). Relationship marketing in bank mutual fund retailing: re-engineering from a sales to an advisory platform. *Academy of Marketing Studies Journal*, *18*, 131–141.

Coval, J. D., & Moskovits, T. J. (2001). The Geography of Investment: Informed Trading and Asset Prices. *The Journal of Political Economy*, *109*, 811–841.

Crawley, M. J. (2014). *Statistics: An Introduction Using R*. Wiley. Retrieved from https://books.google.com/books?id=KR-FBAAAQBAJ&pgis=1

Cremers, K. J. M., & Petajisto, A. (2009). How Active Is Your Fund Manager? A New Measure That Predicts Performance. *Review of Financial Studies*, *22*, 3329–3365.

Cuthbertson, K. (1996). *Quantitative Financial Economics: Stocks , Bonds and Foreign Exchange*. John Wiley & Sons, Inc.

Cuthbertson, K., Nitzsche, D., & O'Sullivan, N. (2010). Mutual Fund Performance : Measurement and evidence. *Financial Markets, Institutions & Instruments*, *19*, 95–187.

Damodaran, A. (2002). *Investment Valuation* (Second).

Damodaran, A. (2006). *Damodaran on valuation: Security Analysis for Investment and Corporate Finance*. *John Willey & Sons, Inc*. doi:10.1016/0263-2373(95)90009-8

Dougherty, C. (2007). *Introduction to Econometrics* (3rd ed.). Oxford University Press.

Easterby-Smith, M., Thorpe, R., & Jackson, P. R. (2012). *Management Research*. SAGE Publications. Retrieved from https://books.google.com/books?id=ahbhMb-R7MQC&pgis=1

Elton, E. J., Gruber, M. J., & Green, T. C. (2007). The Impact of Mutual Fund Family Membership on Investor Risk. *Journal of Financial and Quantitative Analysis*, *42*, 257.

Finanstilsynet. Act on Securities Funds (Securities Funds Act) (2012). Retrieved from http://www.finanstilsynet.no/Global/English/Laws_and_regulations/Securities_market/Securities_Funds_Act.pdf

Gallaher, S., Kaniel, R., & Starks, L. (2006). Madison Avenue meets Wall Street: Mutual fund families, competition and advertising. *Competition and Advertising (…*. Retrieved from http://papers.ssrn.com/sol3/papers.cfm?abstract_id=879775

Gaspar, J. M., Massa, M., & Matos, P. (2006). Favoritism in mutual fund families? Evidence on strategic cross-fund subsidization. *Journal of Finance*, *61*, 73–104.

Graham, B. (2003). The Intelligent Investor: The Definitive Book on Value Investing. (J. Zweig, Ed.). HarperCollins Books.

Guedj, I., & Papastaikoudi, J. (2003). Can Mutual Fund Families Affect the Performance of Their Funds? *October*, *78712*. Retrieved from http://papers.ssrn.com/sol3/papers.cfm?abstract_id=467282&rec=1&srcabs=570381

Harvey, C., & Gray, S. (1997). Portfolio Analysis and Diversification. Retrieved May 15, 2016, from http://people.duke.edu/~charvey/Classes/ba350_1997/diverse/diverse.htm

Hornenes, T. G., Nedrejord, E., & Pham, N.-K. (2015). *En prestasjonsanalyse av norske aksjefond i perioden 2010 -2014*. Høgskolen Stord/Haugesund.

Huang, J., Sialm, C., & Zhang, H. (2011). Risk shifting and mutual fund performance. *Review of Financial Studies*, *24*, 2575–2616.

Huij, J., & Verbeek, M. (2007). Cross-sectional learning and short-run persistence in mutual fund performance. *Journal of Banking and Finance*, *31*, 973–997.

Lintner, J. (1965). The Valuation of Risky Assets and the Selection of Risky Investments in Stock Portfolio and Capital Budgets. *Review of Economics and Statistics*, 13–27.

Markowitz, H. M. (1952). Mean-variance analysis in portfolio choice and capital markets. *Journal of Finance*, *7*, 77–91.

Moen, L. A., & Rønning, T. F. (2010). *Har partnereide aksjefond bedre avkastning enn bankeide ?* Norges Handelshøyskole.

Mossin, J. (1966). Equilibrium in a Capital Asset Market. *Econometrica*, *34*, 768–783.

Palczewski, A. (2008). Portfolio optimization - a practical approach, 4.

Pedersen, H. S., & Vorland, N. K. (2003). *Prestasjonsvurdering av norske aksjefond i perioden 1996-2003*.

Ross, S. A., Westerfield, R. W., & Jaffe, J. F. (2003). *Corporate Finance* (Sixth). The McGraw-Hill / Irwin.

Sharpe, W. F. (1964). Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk. *The Journal of Finance*, 425.

Sharpe, W. F. (1970). *Portfolio Theory and Capital Markets*. New York.

Shawky, J. (1982). An Update on Mutual Funds: Better Grades. *Journal of Portfolio Management*.

Sirri, E., & Tufano, P. (1998). Costly Search and Mutual Funds Flows. *Journal of Finance*, *53*, 1589–1622.

Sølverg, G. (2010). *Hva er sammenhengen mellom bruttoavkastning or forvaltningshonorar hos norske aksjefond?* Høgskolen i Sør-Trondelag.

Spaulding, W. C. (2016). Single Asset Risk: Standard Deviation and Coefficient of Variation.

Retrieved May 6, 2016, from http://thismatter.com/money/investments/single-asset-risk.htm

Spritz, A. E. (1970). Mutual fund performance and cash inflow. *Applied Economics*, *2*, 141–145.

Statistisk sentralbyrå. (2015). Mutual funds, quarterly figures, Q3 2015. Retrieved from https://www.ssb.no/en/bank-og-finansmarked/statistikker/vpfondk/kvartal/2015-11-26#content

Stone, D., & Ellis, J. (2006). Evaluation of Means for small samples - The t-test. Retrieved May 10, 2016, from http://www.chem.utoronto.ca/coursenotes/analsci/stats/ttest.html

U.S. Securities and Exchange Commission. (2010). *Mutual funds: A Guide for Investors*. Washington, DC.

Verdipapirfondenes forening. (2016). Historisk statistikk - VFF. Retrieved May 16, 2016, from http://vff.no/historisk-statistikk

Vidal-García, J. (2013). The persistence of European mutual fund performance. *Research in International Business and Finance*, *28*, 45–67.

Weisstein, E. W. (n.d.). Student's t-Distribution. Wolfram Research, Inc. Retrieved from http://mathworld.wolfram.com/Studentst-Distribution.html

Wright, S. S. (2003). *Getting Started in Bonds* (Second). John Wiley & Sons, Inc.

Zivot, E. (2013). Chapter 1. Introduction to Portfolio Theory. In *Course Econ 424: Computation Finance and Financial Econometrics* (p. 34).

8 APPENDICES

Appendix A CLASSIFICATION OF THE MUTUAL FUNDS AND THEIR ASSIGNED VARIABLE

Data table 1. Mutual fund family by type

Type of fund	Name of the mutual fund	Name of the corresponding variable	Fund number (for calculations)
DNB family of the mutual funds			
Combination	DNB Aktiv 10	da10	1
	DNB Aktiv 100	da100	2
	DNB Aktiv 30	da30	3
	DNB Aktiv 50	da50	4
	DNB Aktiv 80	da80	5
Stock	DNB 2020	d2020	6
	DNB Asia	dasia	7
	DNB Europe	deurop	8
	DNB Finans	dfin	9
	DNB Global	dglob	10
	DNB Global IV	dglob4	11
	DNB Global Emerging Markets	dglem	12
	DNB Healthcare	dhcare	13
	DNB Navigator	dnavg	14
	DNB Norge II	dnorga	15
	DNB Norge Indeks	dnorind	16
	DNB Norge Selectiv II	dnorgsel	17
	DNB Private Equity	dpreq	18
	DNB SMB	dsmb	19
	DNB Likviditet IV	dlik4	21
	DNB USA	dusa	20
Bond	DNB Kredittobligasjon	dkredobl	22
	DNB Obligasjon III	dobl	23
	DNB Obligasjon 20 (IV)	dobl20	24
ODIN family of the mutual funds			
Combination	ODIN Flex	flex	1
	ODIN Horisont	horizt	2
	ODIN Konservativ	okons	3
Stock	ODIN Maritim	omaritim	4
	ODIN Emerging markets	oEM	5
	ODIN Europa	oEurope	6
	ODIN Europa II	oEurope2	7
	ODIN Global	oglobal	8
	ODIN Global II	oglob2	9
	ODIN Norden	onorden	10
	ODIN Norden II	onord2	11
	ODIN Norge	onorge	12
	ODIN Norge II	onorge2	13
Bond	ODIN Obligasjon	ooblig	14
	ODIN Kort obligasjon	okortobl	15
	ODIN Kreditt	okreditt	16

Appendix B DESCRIPTIVE STATISTICS FOR THE MUTUAL FUND FAMILIES AND MARKET

Data table 2. Descriptive statistics for DNB mutual funds family

Name fund by variable	*Maximum return*	*Minimum return*	*Average return*	*Return's variance*	*Standard deviation*	*Sharpe ratio*	*M2*	*Ranking by Sharpe ratio / M2*
da10	1.39%	-1.00%	0.34%	0.00%	0.50%	0.5661	2.26%	5
da100	6.99%	-11.84%	0.95%	0.11%	3.26%	0.2754	1.13%	14
da30	2.41%	-3.73%	0.48%	0.01%	1.04%	0.4074	1.64%	8
da50	3.63%	-6.51%	0.61%	0.03%	1.70%	0.3283	1.33%	11
da80	5.95%	-9.46%	0.81%	0.06%	2.52%	0.3022	1.23%	13
d2020	7.88%	-10.74%	0.29%	0.11%	3.39%	0.0691	0.32%	21
dasia	12.58%	-12.52%	0.74%	0.15%	3.90%	0.1767	0.74%	17
deurop	6.82%	-14.84%	0.75%	0.13%	3.62%	0.1940	0.81%	16
dfin	9.24%	-16.50%	1.14%	0.21%	4.54%	0.2401	0.99%	15
dglob	7.83%	-11.24%	1.17%	0.09%	3.08%	0.3628	1.47%	10
dglob4	7.92%	-11.01%	1.28%	0.09%	3.07%	0.3985	1.61%	9
dglem	9.87%	-12.65%	0.19%	0.18%	4.29%	0.0325	0.18%	22
dhcare	8.46%	-8.48%	1.97%	0.12%	3.39%	0.5656	2.26%	6
dnavg	10.10%	-15.03%	-0.60%	0.31%	5.52%	-0.1179	-0.41%	24
dnorga	9.68%	-10.97%	0.41%	0.16%	4.04%	0.0883	0.40%	19
dnorind	9.75%	-10.63%	0.57%	0.17%	4.16%	0.1238	0.54%	18
dnorgsel	13.00%	-9.94%	0.39%	0.18%	4.30%	0.0779	0.36%	20
dpreq	6.77%	-16.58%	1.23%	0.14%	3.79%	0.3109	1.27%	12
dsmb	14.55%	-15.56%	0.17%	0.34%	5.82%	0.0208	0.13%	23
dusa	8.14%	-9.39%	1.41%	0.10%	3.16%	0.4274	1.72%	7
dlik4	0.79%	-0.71%	0.20%	0.00%	0.20%	0.7260	2.88%	3
dkredobl	1.09%	-1.28%	0.40%	0.00%	0.41%	0.8520	3.37%	1
dobl	1.15%	-1.33%	0.38%	0.00%	0.41%	0.8135	3.22%	2
dobl20	1.21%	-1.50%	0.35%	0.00%	0.45%	0.6581	2.62%	4

Data table 3. . Descriptive statistics of ODIN mutual funds family

Name fund by variable	Maximum return	Minimum return	Average return	Return's variance	Standard deviation	Sharpe ratio	M2	Ranking by Sharpe ratio / M2
flex	3.36%	-6.25%	0.56%	0.030%	1.74%	0.2934	1.20%	6
horizt	4.38%	-9.25%	0.65%	0.065%	2.55%	0.2334	0.96%	11
okons	2.17%	-4.07%	0.43%	0.012%	1.08%	0.3521	1.43%	4
omaritim	9.03%	-18.69%	-0.19%	0.246%	4.96%	-0.0495	-0.14%	16
oEM	8.14%	-14.18%	0.49%	0.157%	3.97%	0.1100	0.48%	13
oEurope	8.41%	-16.07%	1.08%	0.150%	3.87%	0.2657	1.09%	9
oEurope2	8.49%	-15.90%	1.11%	0.148%	3.85%	0.2747	1.12%	8
oglobal	9.03%	-10.11%	1.10%	0.134%	3.65%	0.2874	1.17%	7
oglob2	9.17%	-10.09%	1.19%	0.133%	3.64%	0.3134	1.28%	5
onorden	8.17%	-13.70%	0.87%	0.179%	4.23%	0.1937	0.81%	12
onord2	10.56%	-13.50%	1.13%	0.198%	4.45%	0.2410	0.99%	10
onorge	7.56%	-15.22%	0.16%	0.177%	4.21%	0.0248	0.15%	15
onorge2	7.64%	-15.15%	0.23%	0.175%	4.19%	0.0412	0.21%	14
ooblig	0.72%	-0.70%	0.30%	0.001%	0.27%	0.9386	3.71%	1
okortobl	0.54%	-0.95%	0.18%	0.000%	0.20%	0.6334	2.52%	2
okreditt	2.67%	-3.44%	0.52%	0.014%	1.17%	0.4028	1.62%	3

Data table 4. Descriptive statistics for market

Name fund by variable	Maximum return	Minimum return	Average return	Return's variance	Standard deviation	Sharpe ratio	M2
OSEAX	9.95%	-10.52%	0.52%	0.146%	3.82%	0.1222	0.53%
OSEBX	9.78%	-10.68%	0.60%	0.152%	3.90%	0.1407	0.60%
OSETR	10.20%	-10.86%	0.55%	0.159%	3.99%	0.1236	0.54%
st1x	3.93%	-3.38%	0.24%	0.020%	1.42%	0.1339	0.58%
st2x	7.16%	-7.92%	0.01%	0.041%	2.03%	-0.0224	-0.03%

Appendix C CORRELATION BETWEEN FUNDS

Data table 5. Correlation between mutual fund within DNB family

	da10	*da100*	*da30*	*da50*	*da80*	*d2020*	*dasia*	*deurop*	*dfin*	*dglob*	*dglob4*	*dglem*	*dhcare*	*dnavg*	*dnorga*	*dnorind*	*dnorgsel*	*dpreq*	*dsmb*	*dusa*	*dlik4*	*dkredobl*	*dobl*	*dobl20*
da10		0.75	0.81	0.77	0.76	0.69	0.55	0.64	0.69	0.64	0.63	0.61	0.38	0.58	0.65	0.66	0.62	0.68	0.49	0.57	0.33	0.36	0.39	0.38
da100			0.98	0.99	0.98	0.63	0.75	0.88	0.87	0.92	0.91	0.80	0.62	0.69	0.82	0.82	0.78	0.87	0.73	0.82	0.14	-0.02	0.01	0.00
da30				0.99	0.96	0.61	0.76	0.87	0.84	0.91	0.91	0.79	0.65	0.65	0.78	0.79	0.74	0.87	0.65	0.82	0.25	0.17	0.20	0.19
da50					0.97	0.62	0.76	0.88	0.86	0.93	0.92	0.80	0.65	0.66	0.79	0.79	0.75	0.88	0.68	0.83	0.18	0.07	0.10	0.08
da80						0.60	0.71	0.88	0.86	0.92	0.92	0.76	0.64	0.64	0.75	0.74	0.71	0.87	0.67	0.85	0.14	0.01	0.04	0.04
d2020							0.46	0.52	0.61	0.43	0.42	0.51	0.08	0.63	0.74	0.70	0.72	0.55	0.60	0.33	0.10	-0.07	-0.06	-0.07
dasia								0.56	0.53	0.69	0.69	0.93	0.50	0.43	0.58	0.59	0.54	0.72	0.50	0.58	0.22	0.08	0.08	0.11
deurop									0.90	0.87	0.86	0.63	0.61	0.58	0.70	0.70	0.63	0.78	0.61	0.72	0.11	-0.03	-0.01	-0.02
dfin										0.78	0.78	0.59	0.53	0.60	0.73	0.71	0.68	0.82	0.62	0.68	0.17	-0.02	0.01	0.01
dglob											1.00	0.69	0.79	0.47	0.58	0.59	0.53	0.84	0.53	0.94	0.10	0.05	0.08	0.06
dglob4												0.69	0.79	0.47	0.58	0.59	0.53	0.84	0.52	0.94	0.11	0.05	0.08	0.06
dglem													0.43	0.54	0.69	0.69	0.65	0.69	0.63	0.58	0.19	0.01	0.01	0.03
dhcare														0.05	0.22	0.23	0.14	0.67	0.20	0.80	0.10	0.23	0.23	0.19
dnavg															0.86	0.85	0.84	0.51	0.75	0.36	0.13	-0.18	-0.13	-0.16
dnorga																0.98	0.98	0.61	0.84	0.46	0.16	-0.13	-0.09	-0.10
dnorind																	0.97	0.58	0.81	0.47	0.13	-0.13	-0.10	-0.11
dnorgsel																		0.53	0.82	0.42	0.16	-0.16	-0.12	-0.12
dpreq																			0.53	0.76	0.05	0.10	0.12	0.07
dsmb																				0.43	0.06	-0.28	-0.26	-0.25
dusa																					0.08	0.06	0.08	0.06
dlik4																						0.51	0.53	0.70
dkredobl																							0.99	0.94
dobl																								0.95
dobl20																								

Data table 6. Correlation between mutual fund within ODIN family

	flex	*horizt*	*okons*	*omaritim*	*oEM*	*oEurope*	*oEurope2*	*oglobal*	*oglob2*	*onorden*	*onord2*	*onorge*	*onorge2*	*ooblig*	*okortobl*	*okreditt*
flex		0.99	0.99	0.59	0.85	0.77	0.77	0.87	0.87	0.86	0.83	0.69	0.69	-0.04	0.14	0.65
horizt			0.97	0.61	0.85	0.78	0.78	0.86	0.85	0.87	0.85	0.71	0.71	-0.08	0.10	0.62
okons				0.59	0.85	0.78	0.78	0.84	0.84	0.84	0.81	0.69	0.69	0.03	0.21	0.73
omaritim					0.52	0.73	0.73	0.46	0.47	0.69	0.67	0.76	0.76	-0.13	0.08	0.56
oEM						0.65	0.65	0.75	0.75	0.77	0.71	0.64	0.64	-0.16	-0.01	0.56
oEurope							1.00	0.66	0.67	0.77	0.76	0.78	0.78	0.06	0.20	0.64
oEurope2								0.66	0.67	0.77	0.76	0.78	0.78	0.08	0.21	0.65
oglobal									1.00	0.79	0.76	0.50	0.51	0.01	0.08	0.47
oglob2										0.79	0.76	0.51	0.51	0.02	0.08	0.47
onorden											0.97	0.77	0.77	-0.18	0.05	0.64
onord2												0.75	0.75	-0.15	0.07	0.61
onorge													1.00	-0.15	0.18	0.71
onorge2														-0.14	0.18	0.71
ooblig															0.68	0.19
okortobl																0.42
okreditt																

Data table 7. Correlation between mutual fund outside the family

	flex	horizt	okons	omaritim	oEM	oEurope	oEurope2	oglobal	oglob2	onorden	onord2	onorge	onorge2	ooblig	okortobl	okreditt
da10	0.76	0.76	0.80	0.51	0.61	0.70	0.72	0.71	0.71	0.72	0.70	0.64	0.64	0.39	0.49	0.74
da100	0.80	0.80	0.80	0.71	0.72	0.87	0.88	0.70	0.70	0.81	0.79	0.85	0.85	0.03	0.20	0.67
da30	0.79	0.78	0.80	0.66	0.68	0.87	0.88	0.70	0.70	0.76	0.73	0.79	0.80	0.20	0.32	0.70
da50	0.81	0.81	0.81	0.69	0.71	0.88	0.89	0.71	0.71	0.79	0.76	0.82	0.82	0.10	0.24	0.68
da80	0.80	0.80	0.80	0.67	0.70	0.86	0.87	0.73	0.73	0.79	0.77	0.79	0.79	0.05	0.20	0.65
d2020	0.71	0.72	0.73	0.61	0.71	0.62	0.63	0.51	0.50	0.69	0.67	0.74	0.74	-0.05	0.23	0.67
dasia	0.70	0.69	0.72	0.55	0.73	0.67	0.67	0.60	0.60	0.61	0.58	0.65	0.65	0.05	0.09	0.56
deurop	0.68	0.68	0.68	0.63	0.57	0.87	0.87	0.61	0.61	0.74	0.72	0.72	0.72	0.06	0.24	0.59
dfin	0.70	0.70	0.71	0.69	0.61	0.83	0.84	0.58	0.58	0.78	0.76	0.72	0.72	0.10	0.28	0.62
dglob	0.75	0.73	0.73	0.54	0.65	0.80	0.80	0.72	0.72	0.70	0.68	0.63	0.62	0.08	0.15	0.54
dglob4	0.74	0.73	0.73	0.53	0.65	0.79	0.79	0.72	0.72	0.70	0.67	0.63	0.62	0.08	0.15	0.54
dglem	0.73	0.74	0.74	0.58	0.77	0.68	0.69	0.62	0.62	0.65	0.62	0.73	0.73	0.02	0.12	0.57
dhcare	0.54	0.51	0.54	0.26	0.43	0.56	0.56	0.56	0.56	0.45	0.45	0.29	0.29	0.18	0.12	0.30
dnavg	0.47	0.48	0.46	0.77	0.42	0.57	0.59	0.36	0.36	0.57	0.55	0.78	0.78	-0.08	0.27	0.56
dnorga	0.60	0.61	0.61	0.71	0.58	0.70	0.71	0.43	0.43	0.67	0.66	0.91	0.91	-0.02	0.31	0.64
dnorind	0.59	0.60	0.60	0.67	0.57	0.66	0.68	0.47	0.47	0.69	0.67	0.90	0.90	-0.02	0.29	0.63
dnorgsel	0.55	0.56	0.56	0.66	0.56	0.65	0.66	0.38	0.38	0.61	0.60	0.88	0.88	-0.05	0.30	0.61
dpreq	0.78	0.76	0.80	0.73	0.68	0.85	0.85	0.66	0.66	0.74	0.71	0.68	0.68	0.10	0.13	0.66
dsmb	0.52	0.55	0.52	0.69	0.52	0.64	0.62	0.38	0.39	0.63	0.62	0.84	0.83	-0.13	0.17	0.51
dusa	0.68	0.66	0.66	0.40	0.60	0.66	0.67	0.72	0.72	0.62	0.59	0.51	0.51	0.07	0.12	0.44
dlik4	0.09	0.06	0.15	-0.01	0.08	0.09	0.10	0.10	0.10	-0.02	0.00	0.02	0.02	0.56	0.65	0.24
dkredobl	0.04	-0.01	0.11	-0.21	-0.11	0.02	0.04	0.04	0.04	-0.20	-0.19	-0.20	-0.19	0.83	0.60	0.21
dobl	0.05	0.00	0.12	-0.18	-0.11	0.05	0.08	0.05	0.05	-0.18	-0.17	-0.17	-0.16	0.85	0.63	0.24
dobl20	0.06	0.01	0.12	-0.22	-0.09	0.03	0.05	0.08	0.08	-0.18	-0.17	-0.19	-0.19	0.85	0.64	0.22

Appendix D CORRELATION BETWEEN FUNDS' RESIDUAL

Data table 8. Within DNB family's correlation in residuals

	da10	da100	da30	da50	da80	d2020	dasia	deurop	dfin	dglob	dglob4	dglem	dhcare	dnavg	dnorga	dnorind	dnorgsel	dpreq	dsmb	dusa	dlik4	dkredobl	dobl	dobl20
da10		0.75	0.81	0.77	0.76	0.65	0.55	0.64	0.65	0.64	0.63	0.61	0.38	0.53	0.61	0.62	0.58	0.68	0.45	0.57	0.33	0.32	0.35	0.38
da100			0.98	0.99	0.98	0.57	0.75	0.88	0.82	0.92	0.91	0.80	0.62	0.64	0.78	0.78	0.73	0.87	0.68	0.82	0.14	-0.05	-0.01	0.00
da30				0.99	0.96	0.55	0.76	0.87	0.80	0.91	0.91	0.79	0.65	0.60	0.74	0.75	0.69	0.87	0.60	0.82	0.25	0.14	0.17	0.19
da50					0.97	0.56	0.76	0.88	0.82	0.93	0.92	0.80	0.65	0.61	0.75	0.75	0.70	0.88	0.64	0.83	0.18	0.04	0.07	0.08
da80						0.55	0.71	0.88	0.83	0.92	0.92	0.76	0.64	0.60	0.72	0.71	0.67	0.87	0.63	0.85	0.14	-0.02	0.01	0.04
d2020							0.41	0.49	0.57	0.39	0.39	0.47	0.09	0.55	0.70	0.65	0.68	0.50	0.55	0.29	0.14	-0.07	-0.06	-0.02
dasia								0.56	0.50	0.69	0.69	0.93	0.50	0.38	0.55	0.56	0.50	0.72	0.47	0.58	0.22	0.08	0.08	0.11
deurop									0.88	0.87	0.86	0.63	0.61	0.55	0.68	0.67	0.61	0.78	0.58	0.72	0.11	-0.05	-0.03	-0.02
dfin										0.77	0.76	0.55	0.55	0.55	0.71	0.68	0.65	0.78	0.58	0.66	0.21	-0.03	0.01	0.05
dglob											1.00	0.69	0.79	0.44	0.56	0.57	0.50	0.84	0.50	0.94	0.10	0.04	0.06	0.06
dglob4												0.69	0.79	0.44	0.56	0.57	0.50	0.84	0.50	0.94	0.11	0.04	0.06	0.06
dglem													0.43	0.50	0.65	0.66	0.62	0.69	0.59	0.58	0.19	0.01	0.01	0.03
dhcare														0.06	0.23	0.24	0.15	0.67	0.21	0.80	0.10	0.20	0.20	0.19
dnavg															0.83	0.82	0.82	0.45	0.73	0.32	0.19	-0.19	-0.15	-0.12
dnorga																0.98	0.97	0.55	0.82	0.43	0.20	-0.12	-0.09	-0.06
dnorind																	0.96	0.53	0.79	0.44	0.18	-0.12	-0.09	-0.07
dnorgsel																		0.48	0.81	0.39	0.20	-0.15	-0.11	-0.09
dpreq																			0.48	0.76	0.05	0.07	0.09	0.07
dsmb																				0.40	0.09	-0.28	-0.26	-0.22
dusa																					0.08	0.04	0.06	0.06
dlik4																						0.50	0.52	0.70
dkredobl																							0.99	0.92
dobl																								0.92
dobl20																								

Data table 9. Within ODIN family correlation in residuals

	flex	*horizt*	*okons*	*omaritim*	*oEM*	*oEurope*	*oEurope2*	*oglobal*	*oglob2*	*onorden*	*onord2*	*onorge*	*onorge2*	*ooblig*	*okortobl*	*okreditt*
flex		0.99	0.99	0.55	0.82	0.77	0.77	0.87	0.87	0.83	0.80	0.65	0.65	-0.04	0.14	0.65
horizt			0.97	0.56	0.81	0.78	0.78	0.86	0.85	0.84	0.81	0.67	0.66	-0.08	0.10	0.62
okons				0.55	0.82	0.78	0.78	0.84	0.84	0.81	0.78	0.66	0.66	0.03	0.21	0.73
omaritim					0.47	0.69	0.68	0.41	0.42	0.66	0.62	0.72	0.72	-0.15	0.04	0.53
oEM						0.60	0.60	0.72	0.72	0.75	0.69	0.60	0.60	-0.17	-0.04	0.53
oEurope							1.00	0.66	0.67	0.72	0.71	0.73	0.73	0.06	0.20	0.64
oEurope2								0.66	0.67	0.72	0.71	0.73	0.73	0.08	0.21	0.65
oglobal									1.00	0.76	0.73	0.46	0.46	0.01	0.08	0.47
oglob2										0.76	0.74	0.47	0.47	0.02	0.08	0.47
onorden											0.97	0.75	0.75	-0.19	0.02	0.61
onord2												0.72	0.73	-0.16	0.03	0.58
onorge													1.00	-0.16	0.15	0.69
onorge2														-0.16	0.16	0.69
ooblig															0.68	0.19
okortobl																0.42
okreditt																

Data table 10. Between families' correlation of residuals

	flex	*horizt*	*okons*	*omaritim*	*oEM*	*oEurope*	*oEurope2*	*oglobal*	*oglob2*	*onorden*	*onord2*	*onorge*	*onorge2*	*ooblig*	*okortobl*	*okreditt*
da10	0.76	0.76	0.80	0.45	0.56	0.70	0.72	0.71	0.71	0.68	0.66	0.59	0.60	0.39	0.49	0.74
da100	0.80	0.80	0.80	0.66	0.67	0.87	0.88	0.70	0.70	0.77	0.74	0.80	0.81	0.03	0.20	0.67
da30	0.79	0.78	0.80	0.61	0.64	0.87	0.88	0.70	0.70	0.71	0.69	0.75	0.76	0.20	0.32	0.70
da50	0.81	0.81	0.81	0.63	0.66	0.88	0.89	0.71	0.71	0.75	0.72	0.78	0.78	0.10	0.24	0.68
da80	0.80	0.80	0.80	0.63	0.66	0.86	0.87	0.73	0.73	0.76	0.73	0.76	0.76	0.05	0.20	0.65
d2020	0.67	0.68	0.70	0.54	0.68	0.56	0.56	0.46	0.46	0.66	0.63	0.70	0.70	-0.06	0.20	0.65
dasia	0.70	0.69	0.72	0.52	0.70	0.67	0.67	0.60	0.60	0.58	0.55	0.62	0.62	0.05	0.09	0.56
deurop	0.68	0.68	0.68	0.61	0.54	0.87	0.87	0.61	0.61	0.72	0.70	0.70	0.70	0.06	0.24	0.59
dfin	0.66	0.66	0.67	0.65	0.58	0.79	0.79	0.54	0.55	0.76	0.74	0.69	0.69	0.10	0.26	0.59
dglob	0.75	0.73	0.73	0.51	0.63	0.80	0.80	0.72	0.72	0.68	0.66	0.60	0.60	0.08	0.15	0.54
dglob4	0.74	0.73	0.73	0.51	0.63	0.79	0.79	0.72	0.72	0.68	0.65	0.60	0.60	0.08	0.15	0.54
dglem	0.73	0.74	0.74	0.54	0.74	0.68	0.69	0.62	0.62	0.61	0.59	0.69	0.70	0.02	0.12	0.57
dhcare	0.54	0.51	0.54	0.29	0.45	0.56	0.56	0.56	0.56	0.47	0.47	0.31	0.30	0.18	0.12	0.30
dnavg	0.41	0.42	0.41	0.72	0.35	0.50	0.52	0.29	0.29	0.52	0.49	0.74	0.75	-0.10	0.25	0.53
dnorga	0.55	0.56	0.56	0.66	0.54	0.65	0.65	0.38	0.38	0.63	0.62	0.90	0.90	-0.03	0.29	0.62
dnorind	0.55	0.56	0.56	0.61	0.53	0.61	0.62	0.42	0.42	0.65	0.63	0.89	0.89	-0.02	0.27	0.60
dnorgsel	0.50	0.51	0.51	0.60	0.52	0.59	0.60	0.33	0.33	0.57	0.55	0.87	0.86	-0.05	0.28	0.58
dpreq	0.78	0.76	0.80	0.70	0.64	0.85	0.85	0.66	0.66	0.70	0.66	0.64	0.64	0.10	0.13	0.66
dsmb	0.48	0.50	0.47	0.65	0.48	0.59	0.57	0.34	0.35	0.59	0.58	0.82	0.81	-0.14	0.14	0.48
dusa	0.68	0.66	0.66	0.37	0.57	0.66	0.67	0.72	0.72	0.59	0.57	0.49	0.49	0.07	0.12	0.44
dlik4	0.09	0.06	0.15	0.02	0.10	0.09	0.10	0.10	0.10	0.00	0.03	0.05	0.05	0.56	0.65	0.24
dkredobl	0.00	-0.05	0.08	-0.23	-0.09	-0.01	0.01	0.02	0.03	-0.18	-0.16	-0.22	-0.21	0.81	0.55	0.20
dobl	0.01	-0.05	0.09	-0.20	-0.09	0.02	0.04	0.03	0.03	-0.17	-0.15	-0.19	-0.18	0.83	0.58	0.23
dobl20	0.06	0.01	0.12	-0.19	-0.06	0.03	0.05	0.08	0.08	-0.15	-0.14	-0.16	-0.16	0.85	0.64	0.22

Appendix E TANGENCY PORTFOLIO OF TWO ASSETS FOR THE MUTUAL FUNDS

Data table 11. The set of the tangency portfolio within DNB family

Portfolio №	Stock №	Bond №	Stock weight	Bond weight	Expected return	Average risk	Sharpe	M2	Covariance
D1	6	22	1.82%	98.18%	0.40%	0.41%	0.8619116	3.41%	-0.000010
D2	6	23	1.69%	98.31%	0.38%	0.40%	0.8218363	3.26%	-0.000008
D3	6	24	2.21%	97.79%	0.35%	0.44%	0.6678969	2.66%	-0.000010
D4	7	22	1.33%	98.67%	0.41%	0.41%	0.8586733	3.40%	0.000013
D5	7	23	1.44%	98.56%	0.39%	0.41%	0.8211529	3.25%	0.000013
D6	7	24	1.85%	98.15%	0.36%	0.45%	0.6665181	2.65%	0.000019
D7	8	22	2.85%	97.15%	0.41%	0.41%	0.8800591	3.48%	-0.000005
D8	8	23	2.67%	97.33%	0.39%	0.41%	0.8372589	3.32%	-0.000001
D9	8	24	3.75%	96.25%	0.36%	0.45%	0.6902534	2.74%	-0.000003
D10	9	22	2.69%	97.31%	0.42%	0.42%	0.8910342	3.53%	-0.000005
D11	9	23	2.47%	97.53%	0.40%	0.41%	0.8449251	3.35%	0.000003
D12	9	24	3.38%	96.62%	0.37%	0.46%	0.6980094	2.77%	0.000002
D13	10	22	4.86%	95.14%	0.44%	0.43%	0.9093613	3.60%	0.000007
D14	10	23	4.83%	95.17%	0.42%	0.43%	0.8676365	3.44%	0.000010
D15	10	24	6.89%	93.11%	0.40%	0.48%	0.7336429	2.91%	0.000008
D16	11	22	5.40%	94.60%	0.45%	0.43%	0.9221061	3.65%	0.000007
D17	11	23	5.38%	94.62%	0.43%	0.43%	0.8801666	3.48%	0.000010
D18	11	24	7.61%	92.39%	0.42%	0.49%	0.7492688	2.97%	0.000009
D19	12	22	0.27%	99.73%	0.40%	0.41%	0.8523012	3.38%	0.000002
D20	12	23	0.26%	99.74%	0.38%	0.41%	0.8137706	3.23%	0.000002
D21	12	24	0.17%	99.83%	0.35%	0.45%	0.6581892	2.62%	0.000006
D22	13	22	5.86%	94.14%	0.50%	0.48%	0.9328827	3.69%	0.000032
D23	13	23	6.21%	93.79%	0.48%	0.48%	0.900753	3.56%	0.000032
D24	13	24	9.54%	90.46%	0.50%	0.56%	0.7959878	3.16%	0.000029
D25	14	22	0.29%	99.71%	0.40%	0.41%	0.8525881	3.38%	-0.000040
D26	14	23	0.00%	100.00%	0.38%	0.41%	0.8134742	3.22%	-0.000030
D27	14	24	0.00%	100.00%	0.35%	0.45%	0.6581017	2.62%	-0.000040
D28	15	22	2.29%	97.71%	0.41%	0.40%	0.8751171	3.46%	-0.000021
D29	15	23	1.99%	98.01%	0.39%	0.40%	0.8302256	3.29%	-0.000016
D30	15	24	2.52%	97.48%	0.35%	0.44%	0.6763539	2.69%	-0.000018
D31	16	22	2.62%	97.38%	0.41%	0.40%	0.8844125	3.50%	-0.000022
D32	16	23	2.37%	97.63%	0.39%	0.40%	0.8390599	3.32%	-0.000017
D33	16	24	3.03%	96.97%	0.35%	0.44%	0.6868349	2.73%	-0.000020
D34	17	22	2.35%	97.65%	0.40%	0.40%	0.8797869	3.48%	-0.000029
D35	17	23	2.02%	97.98%	0.38%	0.40%	0.8332668	3.30%	-0.000022
D36	17	24	2.41%	97.59%	0.35%	0.44%	0.6771023	2.69%	-0.000023
D37	18	22	2.90%	97.10%	0.43%	0.43%	0.8815694	3.49%	0.000016

Portfolio №	*Stock №*	*Bond №*	*Stock weight*	*Bond weight*	*Expected return*	*Average risk*	*Sharpe*	*M2*	*Covariance*
D38	18	23	2.85%	97.15%	0.41%	0.42%	0.8408626	3.33%	0.000019
D39	18	24	4.71%	95.29%	0.39%	0.47%	0.7103657	2.82%	0.000011
D40	19	22	2.12%	97.88%	0.40%	0.39%	0.8945396	3.54%	-0.000068
D41	19	23	1.94%	98.06%	0.38%	0.39%	0.8477974	3.36%	-0.000061
D42	19	24	2.07%	97.93%	0.34%	0.43%	0.6845005	2.72%	-0.000064
D43	20	22	5.64%	94.36%	0.46%	0.44%	0.9327527	3.69%	0.000007
D44	20	23	5.64%	94.36%	0.44%	0.44%	0.8906859	3.53%	0.000010
D45	20	24	7.98%	92.02%	0.43%	0.50%	0.7641091	3.03%	0.000009
D46	21	22	55.88%	44.12%	0.29%	0.26%	0.9169286	3.63%	0.000004
D47	21	23	58.69%	41.31%	0.27%	0.25%	0.8844853	3.50%	0.000004
D48	21	24	79.98%	20.02%	0.23%	0.23%	0.7562985	3.00%	0.000006

Data table 12. The set of the tangency portfolios within ODIN family

Portfolio №	*Stock №*	*Bond №*	*Stock weight*	*Bond weight*	*Expected return*	*Average risk*	*Sharpe*	*M2*	*Covariance*
O1	4	14	0.41%	99.59%	0.30%	0.26%	0.9414785	3.72%	-0.000017
O2	4	15	0.00%	100.00%	0.18%	0.20%	0.6334301	2.52%	0.000008
O3	4	16	0.00%	100.00%	0.52%	1.17%	0.4028314	1.62%	0.000327
O4	5	14	1.80%	98.20%	0.31%	0.26%	0.9753464	3.86%	-0.000017
O5	5	15	0.93%	99.07%	0.18%	0.20%	0.6442196	2.56%	-0.000001
O6	5	16	0.00%	100.00%	0.52%	1.17%	0.4028313	1.62%	0.000260
O7	6	14	1.51%	98.49%	0.31%	0.27%	0.9612519	3.80%	0.000006
O8	6	15	1.21%	98.79%	0.19%	0.21%	0.648467	2.58%	0.000016
O9	6	16	0.92%	99.08%	0.53%	1.18%	0.4029392	1.62%	0.000291
O10	7	14	1.50%	98.50%	0.31%	0.27%	0.9605289	3.80%	0.000008
O11	7	15	1.26%	98.74%	0.19%	0.21%	0.6494737	2.59%	0.000017
O12	7	16	1.57%	98.43%	0.53%	1.19%	0.4031307	1.62%	0.000294
O13	8	14	2.09%	97.91%	0.32%	0.27%	0.978165	3.87%	0.000001
O14	8	15	2.09%	97.91%	0.20%	0.22%	0.6759979	2.69%	0.000006
O15	8	16	10.61%	89.39%	0.59%	1.27%	0.4183265	1.68%	0.000199
O16	9	14	2.25%	97.75%	0.32%	0.27%	0.9836646	3.89%	0.000002
O17	9	15	2.33%	97.67%	0.20%	0.22%	0.685505	2.73%	0.000006
O18	9	16	13.48%	86.52%	0.61%	1.32%	0.4266212	1.72%	0.000200
O19	10	14	2.26%	97.74%	0.32%	0.26%	1.0070648	3.98%	-0.000020
O20	10	15	1.25%	98.75%	0.19%	0.21%	0.6546514	2.61%	0.000004
O21	10	16	0.00%	100.00%	0.52%	1.17%	0.4028314	1.62%	0.000316
O22	11	14	2.29%	97.71%	0.32%	0.26%	1.0155776	4.01%	-0.000018
O23	11	15	1.44%	98.56%	0.19%	0.21%	0.6641478	2.64%	0.000006
O24	11	16	0.00%	100.00%	0.52%	1.17%	0.4028314	1.62%	0.000315
O25	12	14	1.08%	98.92%	0.30%	0.26%	0.953173	3.77%	-0.000017
O26	12	15	0.00%	100.00%	0.18%	0.20%	0.6334297	2.52%	0.000015
O27	12	16	0.00%	100.00%	0.52%	1.17%	0.4028314	1.62%	0.000350
O28	13	14	1.17%	98.83%	0.30%	0.26%	0.9555124	3.78%	-0.000016
O29	13	15	0.00%	100.00%	0.18%	0.20%	0.63343	2.52%	0.000016
O30	13	16	0.00%	100.00%	0.52%	1.17%	0.4028314	1.62%	0.000349

Data table 13. The set of the tangency portfolio for the mutual funds form different families

Portfolio №	*Stock №*	*Bond №*	*Stock weight*	*Bond weight*	*Expected return*	*Average risk*	*Sharpe*	*M2*	*Covariance*
DO1	6	14	0.97%	99.03%	0.30%	0.26%	0.946082	3.74%	-0.000005
DO2	6	15	0.00%	100.00%	0.18%	0.20%	0.6334301	2.52%	0.000015
DO3	6	16	0.00%	100.00%	0.52%	1.17%	0.4028314	1.62%	0.000265
DO4	7	14	0.95%	99.05%	0.31%	0.27%	0.9478523	3.75%	0.000005
DO5	7	15	0.99%	99.01%	0.19%	0.21%	0.6446954	2.57%	0.000007
DO6	7	16	0.00%	100.00%	0.52%	1.17%	0.4028314	1.62%	0.000253
DO7	8	14	1.07%	98.93%	0.31%	0.27%	0.9485398	3.75%	0.000006
DO8	8	15	0.37%	99.63%	0.18%	0.20%	0.6347216	2.53%	0.000018
DO9	8	16	0.00%	100.00%	0.52%	1.17%	0.4028314	1.62%	0.000248
DO10	9	14	0.93%	99.07%	0.31%	0.27%	0.9502061	3.76%	0.000012
DO11	9	15	0.47%	99.53%	0.19%	0.21%	0.6364997	2.53%	0.000026
DO12	9	16	0.00%	100.00%	0.52%	1.17%	0.4028314	1.62%	0.000329
DO13	10	14	2.63%	97.37%	0.33%	0.28%	0.9811571	3.88%	0.000007
DO14	10	15	2.94%	97.06%	0.21%	0.23%	0.6888976	2.74%	0.000009
DO15	10	16	21.03%	78.97%	0.66%	1.39%	0.4380188	1.76%	0.000195
DO16	11	14	2.96%	97.04%	0.33%	0.28%	0.9917813	3.92%	0.000007
DO17	11	15	3.36%	96.64%	0.22%	0.23%	0.7039212	2.80%	0.000009
DO18	11	16	26.87%	73.13%	0.73%	1.48%	0.4559695	1.83%	0.000195
DO19	12	14	0.10%	99.90%	0.30%	0.27%	0.9387448	3.71%	0.000002
DO20	12	15	0.00%	100.00%	0.18%	0.20%	0.6334298	2.52%	0.000011
DO21	12	16	0.00%	100.00%	0.52%	1.17%	0.4028314	1.62%	0.000285
DO22	13	14	3.59%	96.41%	0.36%	0.30%	1.0224603	4.04%	0.000016
DO23	13	15	4.90%	95.10%	0.27%	0.27%	0.8033458	3.19%	0.000008
DO24	13	16	39.71%	60.29%	1.10%	1.70%	0.6158747	2.45%	0.000120
DO25	14	14	0.00%	100.00%	0.30%	0.27%	0.9386266	3.71%	-0.000012
DO26	14	15	0.00%	100.00%	0.18%	0.20%	0.6334301	2.52%	0.000030
DO27	14	16	0.00%	100.00%	0.52%	1.17%	0.4028314	1.62%	0.000360
DO28	15	14	0.74%	99.26%	0.30%	0.26%	0.9447268	3.74%	-0.000002
DO29	15	15	0.00%	100.00%	0.18%	0.20%	0.6334301	2.52%	0.000025
DO30	15	16	0.00%	100.00%	0.52%	1.17%	0.4028314	1.62%	0.000302
DO31	16	14	0.95%	99.05%	0.30%	0.27%	0.9491634	3.75%	-0.000002
DO32	16	15	0.00%	100.00%	0.18%	0.20%	0.6334301	2.52%	0.000025
DO33	16	16	0.00%	100.00%	0.52%	1.17%	0.4028313	1.62%	0.000304
DO34	17	14	0.79%	99.21%	0.30%	0.26%	0.9464291	3.74%	-0.000005
DO35	17	15	0.00%	100.00%	0.18%	0.20%	0.6334301	2.52%	0.000026
DO36	17	16	0.00%	100.00%	0.52%	1.17%	0.4028314	1.62%	0.000304
DO37	18	14	1.63%	98.37%	0.32%	0.27%	0.9630549	3.81%	0.000010
DO38	18	15	2.01%	97.99%	0.20%	0.22%	0.6738067	2.68%	0.000010
DO39	18	16	6.62%	93.38%	0.57%	1.27%	0.4073512	1.64%	0.000292

Portfolio №	Stock №	Bond №	Stock weight	Bond weight	Expected return	Average risk	Sharpe	M2	Covariance
DO40	19	14	0.70%	99.30%	0.30%	0.26%	0.9501798	3.76%	-0.000021
DO41	19	15	0.00%	100.00%	0.18%	0.20%	0.6334289	2.52%	0.000020
DO42	19	16	0.00%	100.00%	0.52%	1.17%	0.4028314	1.62%	0.000348
DO43	20	14	3.24%	96.76%	0.34%	0.28%	1.0068633	3.98%	0.000006
DO44	20	15	3.73%	96.27%	0.23%	0.24%	0.727045	2.89%	0.000007
DO45	20	16	30.10%	69.90%	0.79%	1.50%	0.4894839	1.96%	0.000163
DO46	21	14	33.30%	66.70%	0.27%	0.22%	0.9682605	3.83%	0.000003
DO47	21	15	66.63%	33.37%	0.19%	0.18%	0.7563277	3.00%	0.000003
DO48	21	16	94.29%	5.71%	0.22%	0.21%	0.7623464	3.03%	0.000006
OD49	4	22	1.30%	98.70%	0.40%	0.40%	0.8628456	3.42%	-0.000044
OD50	4	23	0.99%	99.01%	0.38%	0.40%	0.8195468	3.25%	-0.000037
OD51	4	24	1.31%	98.69%	0.34%	0.43%	0.665322	2.65%	-0.000049
OD52	5	22	2.39%	97.61%	0.41%	0.40%	0.8761427	3.47%	-0.000018
OD53	5	23	2.45%	97.55%	0.39%	0.40%	0.8384871	3.32%	-0.000018
OD54	5	24	2.80%	97.20%	0.35%	0.44%	0.6799572	2.70%	-0.000016
OD55	6	22	3.03%	96.97%	0.43%	0.42%	0.8874243	3.51%	0.000003
OD56	6	23	2.83%	97.17%	0.40%	0.42%	0.8430871	3.34%	0.000009
OD57	6	24	4.18%	95.82%	0.38%	0.46%	0.7024599	2.79%	0.000005
OD58	7	22	2.96%	97.04%	0.43%	0.42%	0.8849756	3.50%	0.000007
OD59	7	23	2.76%	97.24%	0.40%	0.42%	0.8409431	3.33%	0.000012
OD60	7	24	4.20%	95.80%	0.38%	0.47%	0.7018503	2.79%	0.000008
OD61	8	22	3.26%	96.74%	0.43%	0.42%	0.8881882	3.52%	0.000006
OD62	8	23	3.35%	96.65%	0.41%	0.42%	0.8506143	3.37%	0.000007
OD63	8	24	4.31%	95.69%	0.38%	0.47%	0.6985147	2.78%	0.000013
OD64	9	22	3.61%	96.39%	0.43%	0.42%	0.8959757	3.55%	0.000006
OD65	9	23	3.69%	96.31%	0.41%	0.42%	0.8581171	3.40%	0.000007
OD66	9	24	4.78%	95.22%	0.39%	0.47%	0.7071209	2.81%	0.000014
OD67	10	22	3.82%	96.18%	0.42%	0.40%	0.9290101	3.67%	-0.000035
OD68	10	23	3.74%	96.26%	0.40%	0.40%	0.8851252	3.50%	-0.000032
OD69	10	24	4.51%	95.49%	0.37%	0.44%	0.7290794	2.90%	-0.000033
OD70	11	22	3.98%	96.02%	0.43%	0.40%	0.9446597	3.74%	-0.000034
OD71	11	23	3.92%	96.08%	0.41%	0.40%	0.9006723	3.56%	-0.000031
OD72	11	24	4.81%	95.19%	0.39%	0.44%	0.7478502	2.97%	-0.000033
OD73	12	22	2.20%	97.80%	0.40%	0.40%	0.8752797	3.47%	-0.000035
OD74	12	23	1.89%	98.11%	0.38%	0.39%	0.8300115	3.29%	-0.000029
OD75	12	24	2.39%	97.61%	0.34%	0.43%	0.6762412	2.69%	-0.000037
OD76	13	22	2.31%	97.69%	0.40%	0.40%	0.8775834	3.47%	-0.000034
OD77	13	23	2.01%	97.99%	0.38%	0.39%	0.8320783	3.30%	-0.000028
OD78	13	24	2.58%	97.42%	0.34%	0.43%	0.6792555	2.70%	-0.000035

Appendix F EFFICIENT FRONTIER FOR DNB

```
$weights
      d2020 dasia deurop dfin dglob dglob4 dglem     dhcare      dnavg dnorga dnorind    dnorgsel dpreq        dsmb       dusa
 [1,]     0     0      0    0     0      0     0 0.00000000 0.80585930      0       0 0.000000000     0 0.000000000 0.00000000
 [2,]     0     0      0    0     0      0     0 0.00000000 0.61171859      0       0 0.000000000     0 0.000000000 0.00000000
 [3,]     0     0      0    0     0      0     0 0.00000000 0.41757789      0       0 0.000000000     0 0.000000000 0.00000000
 [4,]     0     0      0    0     0      0     0 0.00000000 0.22343718      0       0 0.000000000     0 0.000000000 0.00000000
 [5,]     0     0      0    0     0      0     0 0.00000000 0.03308737      0       0 0.000000000     0 0.002475692 0.00000000
 [6,]     0     0      0    0     0      0     0 0.05675641 0.00000000      0       0 0.005875524     0 0.006475785 0.01149933
 [7,]     0     0      0    0     0      0     0 0.18021760 0.00000000      0       0 0.002037077     0 0.000000000 0.00000000
 [8,]     0     0      0    0     0      0     0 0.29731085 0.00000000      0       0 0.000000000     0 0.000000000 0.00000000
 [9,]     0     0      0    0     0      0     0 0.41442571 0.00000000      0       0 0.000000000     0 0.000000000 0.00000000
[10,]     0     0      0    0     0      0     0 0.53154056 0.00000000      0       0 0.000000000     0 0.000000000 0.00000000
[11,]     0     0      0    0     0      0     0 0.64865542 0.00000000      0       0 0.000000000     0 0.000000000 0.00000000
[12,]     0     0      0    0     0      0     0 0.76577028 0.00000000      0       0 0.000000000     0 0.000000000 0.00000000
[13,]     0     0      0    0     0      0     0 0.88288514 0.00000000      0       0 0.000000000     0 0.000000000 0.00000000
[14,]     0     0      0    0     0      0     0 0.99999998 0.00000000      0       0 0.000000000     0 0.000000000 0.00000000
          dkredobl      dobl    dobl20
 [1,] 0.000000e+00 0.0000000 0.1941407
 [2,] 0.000000e+00 0.0000000 0.3882814
 [3,] 0.000000e+00 0.0000000 0.5824221
 [4,] 0.000000e+00 0.0000000 0.7765628
 [5,] 0.000000e+00 0.1086935 0.8557435
 [6,] 9.193930e-01 0.0000000 0.0000000
 [7,] 8.177453e-01 0.0000000 0.0000000
 [8,] 7.026892e-01 0.0000000 0.0000000
 [9,] 5.855743e-01 0.0000000 0.0000000
[10,] 4.684594e-01 0.0000000 0.0000000
[11,] 3.513446e-01 0.0000000 0.0000000
[12,] 2.342297e-01 0.0000000 0.0000000
[13,] 1.171149e-01 0.0000000 0.0000000
[14,] 1.874954e-08 0.0000000 0.0000000
```

```
$covRiskBudgets
      d2020 dasia deurop dfin dglob dglob4 dglem    dhcare     dnavg dnorga dnorind      dnorgsel dpreq        dsmb       dusa
 [1,]     0     0      0    0     0      0     0 0.0000000 1.0028148      0       0 0.0000000000     0 0.000000000 0.00000000
 [2,]     0     0      0    0     0      0     0 0.0000000 1.0058133      0       0 0.0000000000     0 0.000000000 0.00000000
 [3,]     0     0      0    0     0      0     0 0.0000000 1.0057749      0       0 0.0000000000     0 0.000000000 0.00000000
 [4,]     0     0      0    0     0      0     0 0.0000000 0.9661569      0       0 0.0000000000     0 0.000000000 0.00000000
 [5,]     0     0      0    0     0      0     0 0.0000000 0.1203063      0       0 0.0000000000     0 0.003512612 0.00000000
 [6,]     0     0      0    0     0      0     0 0.2711200 0.0000000      0       0 0.0041301690     0 0.000989584 0.03816205
 [7,]     0     0      0    0     0      0     0 0.7237597 0.0000000      0       0 0.0006071277     0 0.000000000 0.00000000
 [8,]     0     0      0    0     0      0     0 0.8776445 0.0000000      0       0 0.0000000000     0 0.000000000 0.00000000
 [9,]     0     0      0    0     0      0     0 0.9377572 0.0000000      0       0 0.0000000000     0 0.000000000 0.00000000
[10,]     0     0      0    0     0      0     0 0.9659603 0.0000000      0       0 0.0000000000     0 0.000000000 0.00000000
[11,]     0     0      0    0     0      0     0 0.9811804 0.0000000      0       0 0.0000000000     0 0.000000000 0.00000000
[12,]     0     0      0    0     0      0     0 0.9902510 0.0000000      0       0 0.0000000000     0 0.000000000 0.00000000
[13,]     0     0      0    0     0      0     0 0.9960639 0.0000000      0       0 0.0000000000     0 0.000000000 0.00000000
[14,]     0     0      0    0     0      0     0 1.0000000 0.0000000      0       0 0.0000000000     0 0.000000000 0.00000000
          dkredobl       dobl       dobl20
 [1,] 0.000000e+00 0.00000000 -0.002814845
 [2,] 0.000000e+00 0.00000000 -0.005813314
 [3,] 0.000000e+00 0.00000000 -0.005774943
 [4,] 0.000000e+00 0.00000000  0.033843079
 [5,] 0.000000e+00 0.08851785  0.787663285
 [6,] 6.855982e-01 0.00000000  0.000000000
 [7,] 2.756332e-01 0.00000000  0.000000000
 [8,] 1.223555e-01 0.00000000  0.000000000
 [9,] 6.224282e-02 0.00000000  0.000000000
[10,] 3.403973e-02 0.00000000  0.000000000
[11,] 1.881960e-02 0.00000000  0.000000000
[12,] 9.749027e-03 0.00000000  0.000000000
[13,] 3.936105e-03 0.00000000  0.000000000
[14,] 5.238501e-10 0.00000000  0.000000000
```

```
$targetReturn
              mean            mu
 [1,] -0.0041434362 -0.0041434362
 [2,] -0.0023069516 -0.0023069516
 [3,] -0.0004704669 -0.0004704669
 [4,]  0.0013660177  0.0013660177
 [5,]  0.0032025023  0.0032025023
 [6,]  0.0050389870  0.0050389870
 [7,]  0.0068754716  0.0068754716
 [8,]  0.0087119562  0.0087119562
 [9,]  0.0105484409  0.0105484409
[10,]  0.0123849255  0.0123849255
[11,]  0.0142214101  0.0142214101
[12,]  0.0160578948  0.0160578948
[13,]  0.0178943794  0.0178943794
[14,]  0.0197308637  0.0197308637
```

```
$targetRisk
              Cov       Sigma        CVaR         VaR
 [1,] 0.044390239 0.044390239 0.111128889 0.094300617
 [2,] 0.033558042 0.033558042 0.082868826 0.069695969
 [3,] 0.022792049 0.022792049 0.054608764 0.045091321
 [4,] 0.012267819 0.012267819 0.026348701 0.020486673
 [5,] 0.004365353 0.004365353 0.007751463 0.003720989
 [6,] 0.004769078 0.004769078 0.006935485 0.002958780
 [7,] 0.007638736 0.007638736 0.012266708 0.007748154
 [8,] 0.011121144 0.011121144 0.017819845 0.011280190
 [9,] 0.014808857 0.014808857 0.024411727 0.017837553
[10,] 0.018580244 0.018580244 0.031003610 0.024394917
[11,] 0.022393069 0.022393069 0.037782674 0.028538504
[12,] 0.026229268 0.026229268 0.045493622 0.034575771
[13,] 0.030079898 0.030079898 0.053204570 0.040613038
[14,] 0.033940047 0.033940047 0.060915516 0.046650304
```

```
$minriskPortfolio
Portfolio Weights:
   d2020    dasia   deurop     dfin    dglob   dglob4    dglem   dhcare    dnavg   dnorga  dnorind dnorgsel    dpreq     dsmb
  0.0000   0.0000   0.0000   0.0000   0.0000   0.0000   0.0000   0.0000   0.0000   0.0000   0.0000   0.0000   0.0000   0.0225
    dusa dkredobl     dobl   dobl20
  0.0000   0.2422   0.7353   0.0000

Covariance Risk Budgets:
   d2020    dasia   deurop     dfin    dglob   dglob4    dglem   dhcare    dnavg   dnorga  dnorind dnorgsel    dpreq     dsmb
  0.0000   0.0000   0.0000   0.0000   0.0000   0.0000   0.0000   0.0000   0.0000   0.0000   0.0000   0.0000   0.0000   0.0225
    dusa dkredobl     dobl   dobl20
  0.0000   0.2422   0.7353   0.0000

Target Returns and Risks:
  mean    Cov   CVaR    VaR
0.0039 0.0039 0.0058 0.0015
```

Appendix G EFFICIENT FRONTIER FOR ODIN

$weights

	omaritim	oEM	oEurope	oEurope2	oglobal	oglob2	onorden	onord2	onorge	onorge2	ooblig	okortobl	okreditt
[1,]	0.734573	0.000000000	0	0.000000e+00	0	0.00000000	0	0.00000000	0	0	0.00000000	0.2654270	0.0000000
[2,]	0.469146	0.000000000	0	0.000000e+00	0	0.00000000	0	0.00000000	0	0	0.00000000	0.5308540	0.0000000
[3,]	0.203719	0.000000000	0	0.000000e+00	0	0.00000000	0	0.00000000	0	0	0.00000000	0.7962810	0.0000000
[4,]	0.000000	0.005202368	0	0.000000e+00	0	0.00000000	0	0.00000000	0	0	0.17686921	0.8179284	0.0000000
[5,]	0.000000	0.001147204	0	0.000000e+00	0	0.00000000	0	0.01815801	0	0	0.86346581	0.1172290	0.0000000
[6,]	0.000000	0.000000000	0	3.868954e-03	0	0.07847842	0	0.00000000	0	0	0.79676348	0.0000000	0.1208891
[7,]	0.000000	0.000000000	0	1.605192e-02	0	0.15140327	0	0.00000000	0	0	0.60302593	0.0000000	0.2295189
[8,]	0.000000	0.000000000	0	2.823489e-02	0	0.22432812	0	0.00000000	0	0	0.40928838	0.0000000	0.3381486
[9,]	0.000000	0.000000000	0	4.041786e-02	0	0.29725296	0	0.00000000	0	0	0.21555083	0.0000000	0.4467783
[10,]	0.000000	0.000000000	0	5.260083e-02	0	0.37017781	0	0.00000000	0	0	0.02181327	0.0000000	0.5554081
[11,]	0.000000	0.000000000	0	1.088736e-01	0	0.46142099	0	0.00000000	0	0	0.00000000	0.0000000	0.4297054
[12,]	0.000000	0.000000000	0	1.707404e-01	0	0.55498834	0	0.00000000	0	0	0.00000000	0.0000000	0.2742713
[13,]	0.000000	0.000000000	0	2.326072e-01	0	0.64855569	0	0.00000000	0	0	0.00000000	0.0000000	0.1188371
[14,]	0.000000	0.000000000	0	2.136773e-07	0	0.99999979	0	0.00000000	0	0	0.00000000	0.0000000	0.0000000

$covRiskBudgets

	omaritim	oEM	oEurope	oEurope2	oglobal	oglob2	onorden	onord2	onorge	onorge2	ooblig	okortobl	okreditt
[1,]	0.9985715	0.000000000	0	0.000000e+00	0	0.0000000	0	0.00000000	0	0	0.0000000000	0.001428475	0.00000000
[2,]	0.9941295	0.000000000	0	0.000000e+00	0	0.0000000	0	0.00000000	0	0	0.0000000000	0.005870524	0.00000000
[3,]	0.9634423	0.000000000	0	0.000000e+00	0	0.0000000	0	0.00000000	0	0	0.0000000000	0.036557664	0.00000000
[4,]	0.0000000	0.005727188	0	0.000000e+00	0	0.0000000	0	0.00000000	0	0	0.1830040627	0.811268750	0.00000000
[5,]	0.0000000	0.001838261	0	0.000000e+00	0	0.0000000	0	0.06640444	0	0	0.8608108241	0.070946480	0.00000000
[6,]	0.0000000	0.000000000	0	2.269398e-02	0	0.5051957	0	0.00000000	0	0	0.2500267714	0.000000000	0.22208355
[7,]	0.0000000	0.000000000	0	6.056593e-02	0	0.6286081	0	0.00000000	0	0	0.0573725016	0.000000000	0.25345347
[8,]	0.0000000	0.000000000	0	7.464150e-02	0	0.6531507	0	0.00000000	0	0	0.0168416600	0.000000000	0.25536614
[9,]	0.0000000	0.000000000	0	8.143639e-02	0	0.6599400	0	0.00000000	0	0	0.0046460339	0.000000000	0.25397757
[10,]	0.0000000	0.000000000	0	8.535075e-02	0	0.6620294	0	0.00000000	0	0	0.0002747709	0.000000000	0.25234506
[11,]	0.0000000	0.000000000	0	1.495765e-01	0	0.7011401	0	0.00000000	0	0	0.0000000000	0.000000000	0.14928349
[12,]	0.0000000	0.000000000	0	2.009304e-01	0	0.7243525	0	0.00000000	0	0	0.0000000000	0.000000000	0.07471708
[13,]	0.0000000	0.000000000	0	2.375994e-01	0	0.7361930	0	0.00000000	0	0	0.0000000000	0.000000000	0.02620766
[14,]	0.0000000	0.000000000	0	1.523451e-07	0	0.9999998	0	0.00000000	0	0	0.0000000000	0.000000000	0.00000000

```
$targetReturn
              mean            mu
 [1,] -9.291677e-04 -9.291677e-04
 [2,]  6.152314e-05  6.152314e-05
 [3,]  1.052214e-03  1.052214e-03
 [4,]  2.042905e-03  2.042905e-03
 [5,]  3.033596e-03  3.033596e-03
 [6,]  4.024286e-03  4.024286e-03
 [7,]  5.014977e-03  5.014977e-03
 [8,]  6.005668e-03  6.005668e-03
 [9,]  6.996359e-03  6.996359e-03
[10,]  7.987050e-03  7.987050e-03
[11,]  8.977741e-03  8.977741e-03
[12,]  9.968431e-03  9.968431e-03
[13,]  1.095912e-02  1.095912e-02
[14,]  1.194981e-02  1.194981e-02
```

```
$targetRisk
              Cov       Sigma        CVaR         VaR
 [1,] 0.036496266 0.036496266 0.094937219 0.072229890
 [2,] 0.023391123 0.023391123 0.060562281 0.046607120
 [3,] 0.010365632 0.010365632 0.026196764 0.020428568
 [4,] 0.002001841 0.002001841 0.004304639 0.001346628
 [5,] 0.002486112 0.002486112 0.003297874 0.001036609
 [6,] 0.004555224 0.004555224 0.007315526 0.005462514
 [7,] 0.007962452 0.007962452 0.015931431 0.009419873
 [8,] 0.011616337 0.011616337 0.025777224 0.017196357
 [9,] 0.015341644 0.015341644 0.035623016 0.024972841
[10,] 0.019096620 0.019096620 0.045468809 0.032749325
[11,] 0.022963355 0.022963355 0.053990967 0.036120646
[12,] 0.027018934 0.027018934 0.062345186 0.038933052
[13,] 0.031190921 0.031190921 0.070699404 0.041745458
[14,] 0.036425081 0.036425081 0.079670661 0.054130852
```

```
$minriskPortfolio

Title:
 MV Minimum Variance Portfolio
 Estimator:         covEstimator
 Solver:            solveRquadprog
 Optimize:          minRisk
 Constraints:       LongOnly

Portfolio Weights:
omaritim      oEM  oEurope oEurope2  oglobal   oglob2  onorden   onord2   onorge  onorge2   ooblig okortobl okreditt
  0.0000   0.0044   0.0000   0.0000   0.0000   0.0000   0.0000   0.0000   0.0000   0.0000   0.1286   0.8669   0.0000

Covariance Risk Budgets:
omaritim      oEM  oEurope oEurope2  oglobal   oglob2  onorden   onord2   onorge  onorge2   ooblig okortobl okreditt
  0.0000   0.0044   0.0000   0.0000   0.0000   0.0000   0.0000   0.0000   0.0000   0.0000   0.1286   0.8669   0.0000

Target Returns and Risks:
  mean    Cov   CVaR    VaR
0.0020 0.0020 0.0044 0.001
```

Appendix H EFFICIENT FRONTIER FOR MIXED FUNDS PORTFOLIO

$weights

	d2020	dasia	deurop	dfin	dglob	dglob4	dglem	dhcare	dnavg	dnorga	dnorind	dnorgsel	dpreq	dsmb	dusa	dkredobl	dobl
[1,]	0	0	0	0	0	0	0	0.00000000	0.76432676	0	0	0	0	0	0	0.000000e+00	0
[2,]	0	0	0	0	0	0	0	0.00000000	0.52865352	0	0	0	0	0	0	0.000000e+00	0
[3,]	0	0	0	0	0	0	0	0.00000000	0.29298028	0	0	0	0	0	0	0.000000e+00	0
[4,]	0	0	0	0	0	0	0	0.00000000	0.05730704	0	0	0	0	0	0	0.000000e+00	0
[5,]	0	0	0	0	0	0	0	0.01391668	0.00000000	0	0	0	0	0	0	3.194867e-02	0
[6,]	0	0	0	0	0	0	0	0.06601059	0.00000000	0	0	0	0	0	0	7.046228e-01	0
[7,]	0	0	0	0	0	0	0	0.17360715	0.00000000	0	0	0	0	0	0	7.895952e-01	0
[8,]	0	0	0	0	0	0	0	0.29420502	0.00000000	0	0	0	0	0	0	6.650265e-01	0
[9,]	0	0	0	0	0	0	0	0.41205275	0.00000000	0	0	0	0	0	0	5.567987e-01	0
[10,]	0	0	0	0	0	0	0	0.52990048	0.00000000	0	0	0	0	0	0	4.485710e-01	0
[11,]	0	0	0	0	0	0	0	0.64774821	0.00000000	0	0	0	0	0	0	3.403433e-01	0
[12,]	0	0	0	0	0	0	0	0.76559594	0.00000000	0	0	0	0	0	0	2.321155e-01	0
[13,]	0	0	0	0	0	0	0	0.88288514	0.00000000	0	0	0	0	0	0	1.171149e-01	0
[14,]	0	0	0	0	0	0	0	0.99999998	0.00000000	0	0	0	0	0	0	1.874957e-08	0

	dobl20	omaritim	oEM	oEurope	oEurope2	oglobal	oglob2	onorden	onord2	onorge	onorge2	ooblig	okortobl	okreditt
[1,]	0	0	0	0	0	0	0	0	0.000000000	0	0	0.0000000	0.2356732	0.000000000
[2,]	0	0	0	0	0	0	0	0	0.000000000	0	0	0.0000000	0.4713465	0.000000000
[3,]	0	0	0	0	0	0	0	0	0.000000000	0	0	0.0000000	0.7070197	0.000000000
[4,]	0	0	0	0	0	0	0	0	0.000000000	0	0	0.0000000	0.9426930	0.000000000
[5,]	0	0	0	0	0	0	0	0	0.013929076	0	0	0.7739239	0.1662817	0.000000000
[6,]	0	0	0	0	0	0	0	0	0.023013365	0	0	0.2063532	0.0000000	0.000000000
[7,]	0	0	0	0	0	0	0	0	0.009882656	0	0	0.0000000	0.0000000	0.026914976
[8,]	0	0	0	0	0	0	0	0	0.000000000	0	0	0.0000000	0.0000000	0.040768522
[9,]	0	0	0	0	0	0	0	0	0.000000000	0	0	0.0000000	0.0000000	0.031148523
[10,]	0	0	0	0	0	0	0	0	0.000000000	0	0	0.0000000	0.0000000	0.021528523
[11,]	0	0	0	0	0	0	0	0	0.000000000	0	0	0.0000000	0.0000000	0.011908523
[12,]	0	0	0	0	0	0	0	0	0.000000000	0	0	0.0000000	0.0000000	0.002288523
[13,]	0	0	0	0	0	0	0	0	0.000000000	0	0	0.0000000	0.0000000	0.000000000
[14,]	0	0	0	0	0	0	0	0	0.000000000	0	0	0.0000000	0.0000000	0.000000000

$covRiskBudgets

	d2020	dasia	deurop	dfin	dglob	dglob4	dglem	dhcare	dnavg	dnorga	dnorind	dnorgsel	dpreq	dsmb	dusa	dkredobl	dobl
[1,]	0	0	0	0	0	0	0	0.0000000	0.9968694	0	0	0	0	0	0	0.000000e+00	0
[2,]	0	0	0	0	0	0	0	0.0000000	0.9903760	0	0	0	0	0	0	0.000000e+00	0
[3,]	0	0	0	0	0	0	0	0.0000000	0.9702081	0	0	0	0	0	0	0.000000e+00	0
[4,]	0	0	0	0	0	0	0	0.0000000	0.6896799	0	0	0	0	0	0	0.000000e+00	0
[5,]	0	0	0	0	0	0	0	0.0837352	0.0000000	0	0	0	0	0	0	4.016538e-02	0
[6,]	0	0	0	0	0	0	0	0.3581834	0.0000000	0	0	0	0	0	0	4.946417e-01	0
[7,]	0	0	0	0	0	0	0	0.7049640	0.0000000	0	0	0	0	0	0	2.583949e-01	0
[8,]	0	0	0	0	0	0	0	0.8701544	0.0000000	0	0	0	0	0	0	1.141925e-01	0
[9,]	0	0	0	0	0	0	0	0.9330319	0.0000000	0	0	0	0	0	0	5.856810e-02	0
[10,]	0	0	0	0	0	0	0	0.9632130	0.0000000	0	0	0	0	0	0	3.237060e-02	0
[11,]	0	0	0	0	0	0	0	0.9798758	0.0000000	0	0	0	0	0	0	1.816467e-02	0
[12,]	0	0	0	0	0	0	0	0.9900319	0.0000000	0	0	0	0	0	0	9.654708e-03	0
[13,]	0	0	0	0	0	0	0	0.9960639	0.0000000	0	0	0	0	0	0	3.936105e-03	0
[14,]	0	0	0	0	0	0	0	1.0000000	0.0000000	0	0	0	0	0	0	5.238510e-10	0

	dobl20	omaritim	oEM	oEurope	oEurope2	oglobal	oglob2	onorden	onord2	onorge	onorge2	ooblig	okortobl	okreditt
[1,]	0	0	0	0	0	0	0	0	0.00000000	0	0	0.00000000	0.003130575	0.0000000000
[2,]	0	0	0	0	0	0	0	0	0.00000000	0	0	0.00000000	0.009624001	0.0000000000
[3,]	0	0	0	0	0	0	0	0	0.00000000	0	0	0.00000000	0.029791931	0.0000000000
[4,]	0	0	0	0	0	0	0	0	0.00000000	0	0	0.00000000	0.310320057	0.0000000000
[5,]	0	0	0	0	0	0	0	0	0.04795758	0	0	0.73201201	0.096129839	0.0000000000
[6,]	0	0	0	0	0	0	0	0	0.06608211	0	0	0.08109281	0.000000000	0.0000000000
[7,]	0	0	0	0	0	0	0	0	0.02017795	0	0	0.00000000	0.000000000	0.0164630803
[8,]	0	0	0	0	0	0	0	0	0.00000000	0	0	0.00000000	0.000000000	0.0156530308
[9,]	0	0	0	0	0	0	0	0	0.00000000	0	0	0.00000000	0.000000000	0.0084000169
[10,]	0	0	0	0	0	0	0	0	0.00000000	0	0	0.00000000	0.000000000	0.0044164440
[11,]	0	0	0	0	0	0	0	0	0.00000000	0	0	0.00000000	0.000000000	0.0019595371
[12,]	0	0	0	0	0	0	0	0	0.00000000	0	0	0.00000000	0.000000000	0.0003133912
[13,]	0	0	0	0	0	0	0	0	0.00000000	0	0	0.00000000	0.000000000	0.0000000000
[14,]	0	0	0	0	0	0	0	0	0.00000000	0	0	0.00000000	0.000000000	0.0000000000

```
$targetReturn
               mean            mu
 [1,] -0.0041434362 -0.0041434362
 [2,] -0.0023069516 -0.0023069516
 [3,] -0.0004704669 -0.0004704669
 [4,]  0.0013660177  0.0013660177
 [5,]  0.0032025023  0.0032025023
 [6,]  0.0050389870  0.0050389870
 [7,]  0.0068754716  0.0068754716
 [8,]  0.0087119562  0.0087119562
 [9,]  0.0105484409  0.0105484409
[10,]  0.0123849255  0.0123849255
[11,]  0.0142214101  0.0142214101
[12,]  0.0160578948  0.0160578948
[13,]  0.0178943794  0.0178943794
[14,]  0.0197308637  0.0197308637
```

```
$targetRisk
              Cov       Sigma        CVaR         VaR
 [1,] 0.042358972 0.042358972 0.106499160 0.090802482
 [2,] 0.029477525 0.029477525 0.073609368 0.062699699
 [3,] 0.016626991 0.016626991 0.040719576 0.034596916
 [4,] 0.004108485 0.004108485 0.008859222 0.007206880
 [5,] 0.002584818 0.002584818 0.003721908 0.001262343
 [6,] 0.004655138 0.004655138 0.007376340 0.004548588
 [7,] 0.007612247 0.007612247 0.012654714 0.007781988
 [8,] 0.011111738 0.011111738 0.018154767 0.010908392
 [9,] 0.014804734 0.014804734 0.024550863 0.017190929
[10,] 0.018578675 0.018578675 0.031099774 0.023947998
[11,] 0.022392671 0.022392671 0.037873724 0.028679206
[12,] 0.026229255 0.026229255 0.045511119 0.034602811
[13,] 0.030079898 0.030079898 0.053204570 0.040613038
[14,] 0.033940047 0.033940047 0.060915516 0.046650304
```

```
$minriskPortfolio

Portfolio Weights:
   d2020    dasia   deurop     dfin    dglob   dglob4    dglem   dhcare    dnavg   dnorga  dnorind dnorgsel    dpreq     dsmb
  0.0000   0.0000   0.0000   0.0000   0.0000   0.0000   0.0000   0.0000   0.0000   0.0000   0.0000   0.0000   0.0000   0.0000
    dusa dkredobl     dobl   dobl20 omaritim      oEM  oEurope oEurope2  oglobal   oglob2  onorden   onord2   onorge  onorge2
  0.0000   0.0000   0.0000   0.0000   0.0000   0.0044   0.0000   0.0000   0.0000   0.0000   0.0000   0.0000   0.0000   0.0000
  ooblig okortobl okreditt
  0.1286   0.8669   0.0000

Covariance Risk Budgets:
   d2020    dasia   deurop     dfin    dglob   dglob4    dglem   dhcare    dnavg   dnorga  dnorind dnorgsel    dpreq     dsmb
  0.0000   0.0000   0.0000   0.0000   0.0000   0.0000   0.0000   0.0000   0.0000   0.0000   0.0000   0.0000   0.0000   0.0000
    dusa dkredobl     dobl   dobl20 omaritim      oEM  oEurope oEurope2  oglobal   oglob2  onorden   onord2   onorge  onorge2
  0.0000   0.0000   0.0000   0.0000   0.0000   0.0044   0.0000   0.0000   0.0000   0.0000   0.0000   0.0000   0.0000   0.0000
  ooblig okortobl okreditt
  0.1286   0.8669   0.0000

Target Returns and Risks:
  mean    Cov   CVaR    VaR
0.0020 0.0020 0.0044 0.0014
```

Appendix I TANGENCY PORTFOLIOS ASSESSMENT

For DNB

```
> print(tangen.d)

Title:
 MV Tangency Portfolio
 Estimator:         covEstimator
 Solver:            solveRquadprog
 Optimize:          minRisk
 Constraints:       LongOnly

Portfolio Weights:
   d2020    dasia   deurop     dfin    dglob   dglob4    dglem   dhcare
  0.0000   0.0000   0.0000   0.0000   0.0000   0.0000   0.0000   0.0353
   dnavg   dnorga  dnorind dnorgsel    dpreq     dsmb     dusa dkredobl
  0.0000   0.0000   0.0000   0.0006   0.0000   0.0122   0.0157   0.9362
    dobl   dobl20
  0.0000   0.0000

Covariance Risk Budgets:
   d2020    dasia   deurop     dfin    dglob   dglob4    dglem   dhcare
  0.0000   0.0000   0.0000   0.0000   0.0000   0.0000   0.0000   0.1612
   dnavg   dnorga  dnorind dnorgsel    dpreq     dsmb     dusa dkredobl
  0.0000   0.0000   0.0000   0.0005   0.0000   0.0035   0.0507   0.7841
    dobl   dobl20
  0.0000   0.0000

Target Returns and Risks:
  mean    Cov   CVaR    VaR
0.0047 0.0044 0.0062 0.0019
```

For ODIN

```
> print(tangen.o)

Title:
 MV Tangency Portfolio
 Estimator:         covEstimator
 Solver:            solveRquadprog
 Optimize:          minRisk
 Constraints:       LongOnly

Portfolio Weights:
omaritim      oEM  oEurope oEurope2  oglobal   oglob2  onorden   onord2
  0.0000   0.0000   0.0000   0.0000   0.0000   0.0000   0.0000   0.0229
  onorge  onorge2   ooblig okortobl okreditt
  0.0000   0.0000   0.9771   0.0000   0.0000

Covariance Risk Budgets:
omaritim      oEM  oEurope oEurope2  oglobal   oglob2  onorden   onord2
  0.0000   0.0000   0.0000   0.0000   0.0000   0.0000   0.0000   0.0917
  onorge  onorge2   ooblig okortobl okreditt
  0.0000   0.0000   0.9083   0.0000   0.0000

Target Returns and Risks:
  mean    Cov   CVaR    VaR
0.0032 0.0026 0.0034 0.0011
```

For Mixed portfolio

```
> print(tangen.f)

Title:
 MV Tangency Portfolio
 Estimator:         covEstimator
 Solver:            solveRquadprog
 Optimize:          minRisk
 Constraints:       LongOnly

Portfolio Weights:
   d2020    dasia   deurop     dfin    dglob   dglob4    dglem   dhcare
  0.0000   0.0000   0.0000   0.0000   0.0000   0.0000   0.0000   0.0214
   dnavg   dnorga  dnorind dnorgsel    dpreq     dsmb     dusa dkredobl
  0.0000   0.0000   0.0000   0.0000   0.0000   0.0000   0.0000   0.1509
    dobl   dobl20 omaritim      oEM  oEurope oEurope2  oglobal   oglob2
  0.0000   0.0000   0.0000   0.0000   0.0000   0.0000   0.0000   0.0000
 onorden   onord2   onorge  onorge2   ooblig okortobl okreditt
  0.0000   0.0181   0.0000   0.0000   0.8097   0.0000   0.0000

Covariance Risk Budgets:
   d2020    dasia   deurop     dfin    dglob   dglob4    dglem   dhcare
  0.0000   0.0000   0.0000   0.0000   0.0000   0.0000   0.0000   0.1304
   dnavg   dnorga  dnorind dnorgsel    dpreq     dsmb     dusa dkredobl
  0.0000   0.0000   0.0000   0.0000   0.0000   0.0000   0.0000   0.1683
    dobl   dobl20 omaritim      oEM  oEurope oEurope2  oglobal   oglob2
  0.0000   0.0000   0.0000   0.0000   0.0000   0.0000   0.0000   0.0000
 onorden   onord2   onorge  onorge2   ooblig okortobl okreditt
  0.0000   0.0614   0.0000   0.0000   0.6398   0.0000   0.0000

Target Returns and Risks:
  mean    Cov   CVaR    VaR
0.0037 0.0030 0.0041 0.0011
```

Appendix J R SCRIPT WITH CODE FOR MASTER THESIS

```
library(zoo)
#### Create data set of returns in zoo format with weekly data
### For DNB family
d_n_b <- read.csv("D:/Docs/YandexDisk/NORD universitetet/edge/fd_n_b.csv")
attach(d_n_b)
## extracting dates
days<-matrix(NA, nrow=60, ncol=1)
for(i in 1:60) days[i,1]<-as.Date(d_n_b[i,1], "%m/%d/%Y")
ddd<-cbind(da10, da100, da30, da50, da80, d2020, dasia, deurop, dfin, dglob, dglob4, dglem,
    dhcare,  dnavg, dnorga, dnorind, dnorgsel, dpreq, dsmb, dusa, dlik4, dkredobl, dobl,
    dobl20)
dd2<-matrix(NA, ncol=24, nrow=60)
colnames(dd2)<-c("da10", "da100", "da30", "da50", "da80","d2020", "dasia", "deurop", "dfin",
    "dglob", "dglob4", "dglem", "dhcare",  "dnavg", "dnorga", "dnorind", "dnorgsel", "dpreq",
    "dsmb", "dusa", "dlik4","dkredobl", "dobl", "dobl20")
for (j in 1:24) for(i in 1:60) dd2[i,j]<-log(ddd[i,j])
D_nb<-zoo(dd2, (as.Date(days)))
DNB<-diff(D_nb) # generating returns
View(DNB)
d<-list(1:5, 6:21, 22:24)
#########################
### For ODIN family
od_in <- read.csv("D:/Docs/YandexDisk/NORD universitetet/edge/fod_in.csv")
attach(od_in)
ooo<-cbind(flex, horizt, okons, omaritim, oEM, oEurope, oEurope2,  oglobal, oglob2, onorden,
    onord2, onorge, onorge2, ooblig,  okortobl, okreditt)
oo2<-matrix(NA, ncol=16, nrow=60)
colnames(oo2)<-c("flex", "horizt", "okons", "omaritim", "oEM", "oEurope", "oEurope2",
    "oglobal", "oglob2",  "onorden", "onord2", "onorge", "onorge2", "ooblig", "okortobl",
    "okreditt")
for (j in 1:16) for(i in 1:60) oo2[i,j]<-log(ooo[i,j])
Od_in<-zoo(oo2, as.Date(days))
ODIN<-diff(Od_in) # generating returns
View(ODIN)
o<-list(1:3, 4:13, 14:16)
detach(od_in, d_n_b)

####### Creating market data
mark <- read.csv("D:/Docs/YandexDisk/NORD universitetet/edge/fmarket.csv")
attach(mark)
Mark<- cbind(OSEAX, OSEBX, OSETR, st1x, st2x)
mark2<-matrix(NA,ncol=5, nrow=60)
colnames(mark2)<-c("OSEAX", "OSEBX", "OSETR", "st1x","st2x")
for(j in 1:5) for(i in 1:60) mark2[i,j]<-log(Mark[i,j])
ma_rk<-zoo(mark2, as.Date(days))
MARKET<-diff(ma_rk) # generating returns
View(MARKET)

############## aggregating data into monthly data
DNB.m<-aggregate(DNB, as.yearmon, sum)
ODIN.m<-aggregate(ODIN, as.yearmon, sum)
SB.m<-aggregate(MARKET, as.yearmon, sum)

######Data for FFM
FF.model <- read.delim("D:/Docs/YandexDisk/NORD universitetet/edge/FF model")
attach(FF.model)
FFM<-zoo(FF.model[, colnames(FF.model) != "X"], yearmon(index(DNB.m)))
View(FFM)

### defining new Risk-free and excess market returns
```

```
rft<-mean(FFM[,4])
SB.mt<-zoo(SB.m, yearmon(index(SB.m)))
for(i in 1:59) for(j in 1:5) SB.mt[i,j]<-SB.m[i,j]-rft

# #### Performing descriptive analysis
descr_dnb.m<-matrix(NA, ncol=24, nrow=5) # for DNB
colnames(descr_dnb.m)<-colnames(DNB)
rownames(descr_dnb.m)<-c("max", "min", "mean","var", "sd")
for(i in 1:24){
 descr_dnb.m[1,i]<-max(DNB.m[,i])
 descr_dnb.m[2,i]<-min(DNB.m[,i])
 descr_dnb.m[3,i]<-mean(DNB.m[,i])
 descr_dnb.m[4,i]<-var(DNB.m[,i])
 descr_dnb.m[5,i]<-(descr_dnb.m[4,i])^(0.5)
}

descr_odin.m<-matrix(NA, ncol=16, nrow=5) # for ODIN
colnames(descr_odin.m)<-colnames(ODIN)
rownames(descr_odin.m)<-c("max", "min", "mean","var", "sd")
for(i in 1:16){
 descr_odin.m[1,i]<-max(ODIN.m[,i])
 descr_odin.m[2,i]<-min(ODIN.m[,i])
 descr_odin.m[3,i]<-mean(ODIN.m[,i])
 descr_odin.m[4,i]<-var(ODIN.m[,i])
 descr_odin.m[5,i]<-(descr_odin.m[4,i])^(0.5)
}

descr_SB.m<-matrix(NA, ncol=5, nrow=5) #for market
colnames(descr_SB.m)<-colnames(MARKET)
rownames(descr_SB.m)<-c("max", "min", "mean","var", "sd")
for(i in 1:5){
 descr_SB.m[1,i]<-max(SB.m[,i])
 descr_SB.m[2,i]<-min(SB.m[,i])
 descr_SB.m[3,i]<-mean(SB.m[,i])
 descr_SB.m[4,i]<-var(SB.m[,i])
 descr_SB.m[5,i]<-(descr_SB.m[4,i])^(0.5)
}

########################
####### Regression on FFM
### for DNB
rm(res.dnb.mf)
res.dnb.mf<-zoo(0, yearmon(index(SB.m)))

for(i in 1:24){
 lm1<-lm (DNB.m[,i]-rft ~ FFM[,1]+FFM[,2]+FFM[,3])
 a<-summary.lm(lm1)$coefficients[2,4]
 b<-summary.lm(lm1)$coefficients[3,4]
 c<-summary.lm(lm1)$coefficients[4,4]
 if ((a>0.05) & (b>0.05)& (c>0.05)) lm2<-lm(DNB.m[,i]-rft~ 1)
 else if ((a>0.05)&(b>0.05))lm2<-lm (DNB.m[,i]-rft ~ FFM[,3])
 else if ((a>0.05)&(c>0.05)) lm2<-lm (DNB.m[,i]-rft ~ FFM[,2])
 else if ((b>0.05)&(c>0.05)) lm2<-lm (DNB.m[,i]-rft ~ FFM[,1])
 else if (a>0.05)lm2<-lm (DNB.m[,i]-rft ~ FFM[,2]+FFM[,3])
 else if (b>0.05) lm2<-lm (DNB.m[,i]-rft ~ FFM[,1]+FFM[,3])
 else if (c>0.05) lm2<-lm (DNB.m[,i]-rft ~ FFM[,1]+FFM[,2])
 else lm2<-lm (DNB.m[,i]-rft ~ FFM[,1]+FFM[,2]+FFM[,3])
 res.dnb.mf<- cbind(res.dnb.mf, summary.lm(lm2)$residuals)
}
res.Dnb.mf <- res.dnb.mf[, ! colnames(res.dnb.mf) %in% c("res.dnb.mf")]
colnames(res.Dnb.mf)<- colnames(DNB.m)
View(res.Dnb.mf)
#### regression for ODIN
rm(res.odin.mf)
res.odin.mf<-zoo(NA, yearmon(index(SB.m)))
```

```
for(i in 1:16) {
 lm1<-lm (ODIN.m[,i]-rft ~ FFM[,1]+FFM[,2]+FFM[,3])
 a<-summary.lm(lm1)$coefficients[2,4]
 b<-summary.lm(lm1)$coefficients[3,4]
 c<-summary.lm(lm1)$coefficients[4,4]
 if ((a>0.05) & (b>0.05)& (c>0.05)) lm2<-lm(ODIN.m[,i]-rft~ 1)
 else if ((a>0.05)&(b>0.05))lm2<-lm (ODIN.m[,i]-rft ~ FFM[,3])
 else if ((a>0.05)&(c>0.05)) lm2<-lm (ODIN.m[,i]-rft ~ FFM[,2])
 else if ((b>0.05)&(c>0.05)) lm2<-lm (ODIN.m[,i]-rft ~ FFM[,1])
 else if ((a>0.05))lm2<-lm (ODIN.m[,i]-rft ~ FFM[,2]+FFM[,3])
 else if (b>0.05) lm2<-lm (ODIN.m[,i]-rft ~ FFM[,1]+FFM[,3])
 else if ((c>0.05)) lm2<-lm (ODIN.m[,i]-rft ~ FFM[,1]+FFM[,2])
 else lm2<-lm (ODIN.m[,i]-rft ~ FFM[,1]+FFM[,2]+FFM[,3])
 res.odin.mf<- cbind(res.odin.mf, summary.lm(lm2)$residuals)
}
res.Odin.mf <- res.odin.mf[, ! colnames(res.odin.mf) %in% c("res.odin.mf")]
colnames(res.Odin.mf)<- colnames(ODIN.m)
View(res.Odin.mf)

##########  Correlation in DNB
cor.in.dnb.m<-cor(DNB.m)
cor.in.dnb.m[lower.tri(cor.in.dnb.m)]<-NA
diag(cor.in.dnb.m)<-NA
View(cor.in.dnb.m)

cor.in.dnb.res.mf<-cor(res.Dnb.mf)
cor.in.dnb.res.mf[lower.tri(cor.in.dnb.res.mf)]<-NA
diag(cor.in.dnb.res.mf)<-NA
View(cor.in.dnb.res.mf)

res.weight.dnb.mf<-matrix(NA, nrow=24, ncol=24)
colnames(res.weight.dnb.mf)<-colnames(res.Dnb.mf)
rownames(res.weight.dnb.mf)<-colnames(res.Dnb.mf)
for (i in 0:22) {for (j in 1+i:22) res.weight.dnb.mf[i+1,j+1]<-
    cor.in.dnb.res.mf[i+1,j+1]/cor.in.dnb.m[i+1, j+1]}
View(res.weight.dnb.mf)

######## Correlation in Odin
cor.in.odin.m<-cor(ODIN.m)
cor.in.odin.m[lower.tri(cor.in.odin.m)]<-NA
diag(cor.in.odin.m)<-NA
View(cor.in.odin.m)

cor.in.odin.res.mf<-cor(res.Odin.mf)
cor.in.odin.res.mf[lower.tri(cor.in.odin.res.mf)]<-NA
diag(cor.in.odin.res.mf)<-NA
View(cor.in.odin.res.mf)

res.weight.odin.mf<-matrix(NA, nrow=16, ncol=16) # calcualtion of weight of residuals
    correaltion in total correaltion
colnames(res.weight.odin.mf)<-colnames(res.Odin.mf)
rownames(res.weight.odin.mf)<-colnames(res.Odin.mf)
for (i in 0:14) {for (j in 1+i:14) res.weight.odin.mf[i+1,j+1]<-
    cor.in.odin.res.mf[i+1,j+1]/cor.in.odin.m[i+1, j+1]}
View(res.weight.odin.mf)

######### COrelation between funds
cor.in.fund.m<-cor(DNB.m,ODIN.m)
cor.in.fund.res.mf<-cor(res.Dnb.mf, res.Odin.mf)

res.weight.fund.mf<-matrix(NA, nrow=24, ncol=16)
colnames(res.weight.fund.mf)<-colnames(res.Odin)
rownames(res.weight.fund.mf)<-colnames(res.Dnb)
```

```
for (i in 0:23) {for (j in 0:15) res.weight.fund.mf[i+1,j+1]<-
    cor.in.fund.res.mf[i+1,j+1]/cor.in.fund.m[i+1, j+1]}
View(res.weight.fund.mf)


##### correlation summary within DNB
cor.agg.D<-matrix(NA,ncol=6, nrow=300)
colnames(cor.agg.D)<-c("d.cc", "d.ss", "d.bb", "d.cs", "d.cb", "d.sb")
v=1 ### fill all comb-comb correlation
for(i in d[[1]]) for(j in d[[1]]){
 cor.agg.D[v,1]<-cor.in.dnb.m[i,j]
 v<-v+1
}
v<-1 ##fill all comb-stock correlation
for(i in d[[1]]) for(j in d[[2]]){
 cor.agg.D[v,4]<-cor.in.dnb.m[i,j]
 v<-v+1
}
v<-1 ### fill all comb-bond correlation
for(i in d[[1]]) for(j in d[[3]]){
 cor.agg.D[v,5]<-cor.in.dnb.m[i,j]
 v<-v+1
}
V=1 ## fill all stock-stock correlation
for(i in d[[2]]) for(j in d[[2]]) {
 cor.agg.D[v,2]<-cor.in.dnb.m[i,j]
 v<-v+1
}
v=1 ## fill all stock-bond correlation
for(i in d[[2]]) for(j in d[[3]]){
 cor.agg.D[v,6]<-cor.in.dnb.m[i,j]
 v<-v+1
}
v=1 ## fill all bond-bond correlation
for(i in d[[3]]) for(j in d[[3]]){
 cor.agg.D[v,3]<-cor.in.dnb.m[i,j]
 v<-v+1
}

##### correlation summary for residual in DNB - FFM
cor.agg.rDf<-matrix(NA,ncol=6, nrow=300)
colnames(cor.agg.rDf)<-c("rdf.cc", "rdf.ss", "rdf.bb", "rdf.cs", "rdf.cb", "rdf.sb")
v=1 ### fill all comb-comb correlation
for(i in d[[1]]) for(j in d[[1]]){
 cor.agg.rDf[v,1]<-cor.in.dnb.res.mf[i,j]
 v<-v+1
}
v=1 ##fill all comb-stock correlation
for(i in d[[1]]) for(j in d[[2]]){
 cor.agg.rDf[v,4]<-cor.in.dnb.res.mf[i,j]
 v<-v+1
}
v=1 ### fill all comb-bond correlation
for(i in d[[1]]) for(j in d[[3]]){
 cor.agg.rDf[v,5]<-cor.in.dnb.res.mf[i,j]
 v<-v+1
}
V=1 ## fill all stock-stock correlation
for(i in d[[2]]) for(j in d[[2]]) {
 cor.agg.rDf[v,2]<-cor.in.dnb.res.mf[i,j]
 v<-v+1
}
v=1 ## fill all stock-bond correlation
for(i in d[[2]]) for(j in d[[3]]){
 cor.agg.rDf[v,6]<-cor.in.dnb.res.mf[i,j]
```

```
 v<-v+1
}
v=1 ## fill all bond-bond correlation
for(i in d[[3]]) for(j in d[[3]]){
 cor.agg.rDf[v,3]<-cor.in.dnb.res.mf[i,j]
 v<-v+1
}


######################################################################
##### correlation summary within ODIN
cor.agg.O<-matrix(NA,ncol=6, nrow=300)
colnames(cor.agg.O)<-c("o.cc", "o.ss", "o.bb", "o.cs", "o.cb", "o.sb")
v=1 ### fill all comb-comb correlation
for(i in o[[1]]) for(j in o[[1]]){
 cor.agg.O[v,1]<-cor.in.odin.m[i,j]
 v<-v+1
}
v=1 ##fill all comb-stock correlation
for(i in o[[1]]) for(j in o[[2]]){
 cor.agg.O[v,4]<-cor.in.odin.m[i,j]
 v<-v+1
}
v=1 ### fill all comb-bond correlation
for(i in o[[1]]) for(j in o[[3]]){
 cor.agg.O[v,5]<-cor.in.odin.m[i,j]
 v<-v+1
}
V=1 ## fill all stock-stock correlation
for(i in o[[2]]) for(j in o[[2]]) {
 cor.agg.O[v,2]<-cor.in.odin.m[i,j]
 v<-v+1
}
v=1 ## fill all stock-bond correlation
for(i in o[[2]]) for(j in o[[3]]){
 cor.agg.O[v,6]<-cor.in.odin.m[i,j]
 v<-v+1
}
v=1 ## fill all bond-bond correlation
for(i in o[[3]]) for(j in o[[3]]){
 cor.agg.O[v,3]<-cor.in.odin.m[i,j]
 v<-v+1
}

##### correlation summary for residual in ODIN - FFM
cor.agg.rOf<-matrix(NA,ncol=6, nrow=300)
colnames(cor.agg.rOf)<-c("rof.cc", "rof.ss", "rof.bb", "rof.cs", "rof.cb", "rof.sb")
v=1 ### fill all comb-comb correlation
for(i in o[[1]]) for(j in o[[1]]){
 cor.agg.rOf[v,1]<-cor.in.odin.res.mf[i,j]
 v<-v+1
}
v=1 ##fill all comb-stock correlation
for(i in o[[1]]) for(j in o[[2]]){
 cor.agg.rOf[v,4]<-cor.in.odin.res.mf[i,j]
 v<-v+1
}
v=1 ### fill all comb-bond correlation
for(i in o[[1]]) for(j in o[[3]]){
 cor.agg.rOf[v,5]<-cor.in.odin.res.mf[i,j]
 v<-v+1
}
V=1 ## fill all stock-stock correlation
for(i in o[[2]]) for(j in o[[2]]) {
 cor.agg.rOf[v,2]<-cor.in.odin.res.mf[i,j]
```

```
 v<-v+1
}
v=1 ## fill all stock-bond correlation
for(i in o[[2]]) for(j in o[[3]]){
 cor.agg.r0f[v,6]<-cor.in.dnb.res.mf[i,j]
 v<-v+1
}
v=1 ## fill all bond-bond correlation
for(i in o[[3]]) for(j in o[[3]]){
 cor.agg.r0f[v,3]<-cor.in.odin.res.mf[i,j]
 v<-v+1
}

###### Correlation between fund family
#### monthly return
cor.agg.fund<-matrix(NA, ncol=6, nrow=150)
colnames(cor.agg.fund)<-c("f.cc", "f.ss", "f.bb", "f.cs", "f.cb", "f.sb")
v=1 ### fill all comb-comb
for(i in d[[1]]) for(j in o[[1]]){
 cor.agg.fund[v,1]<-cor.in.fund.m[i,j]
 v<-v+1
}
v<-1 ### fill all stock stock
for(i in d[[2]]) for(j in o[[2]]){
 cor.agg.fund[v,2]<-cor.in.fund.m[i,j]
 v<-v+1
}
v<-1 ### fill all bond bond
for(i in d[[3]]) for(j in o[[3]]){
 cor.agg.fund[v,3]<-cor.in.fund.m[i,j]
 v<-v+1
}
v<-1 ### fill all comb stock
for(i in d[[1]]) for(j in o[[2]]){
 cor.agg.fund[v,4]<-cor.in.fund.m[i,j]
 v<-v+1
}
for(i in d[[2]]) for(j in o[[1]]){
 cor.agg.fund[v,4]<-cor.in.fund.m[i,j]
 v<-v+1
}
v<-1 ### fill all comb bond
for(i in d[[1]]) for(j in o[[3]]){
 cor.agg.fund[v,5]<-cor.in.fund.m[i,j]
 v<-v+1
}
for(i in d[[3]]) for(j in o[[1]]){
 cor.agg.fund[v,5]<-cor.in.fund.m[i,j]
 v<-v+1
}
v<-1 ### fill all stock bond
for(i in d[[2]]) for(j in o[[3]]){
 cor.agg.fund[v,6]<-cor.in.fund.m[i,j]
 v<-v+1
}
for(i in d[[3]]) for(j in o[[2]]){
 cor.agg.fund[v,5]<-cor.in.fund.m[i,j]
 v<-v+1
}

#### FFM residuals correlation
cor.agg.fund.rf<-matrix(NA, ncol=6, nrow=150)
colnames(cor.agg.fund.r)<-c("f.cc", "f.ss", "f.bb", "f.cs", "f.cb", "f.sb")
v=1 ### fill all comb-comb
for(i in d[[1]]) for(j in o[[1]]){
```

```
 cor.agg.fund.rf[v,1]<-cor.in.fund.res.mf[i,j]
 v<-v+1
}
v<-1 ### fill all stock stock
for(i in d[[2]]) for(j in o[[2]]){
 cor.agg.fund.rf[v,2]<-cor.in.fund.res.mf[i,j]
 v<-v+1
}
v<-1 ### fill all bond bond
for(i in d[[3]]) for(j in o[[3]]){
 cor.agg.fund.rf[v,3]<-cor.in.fund.res.mf[i,j]
 v<-v+1
}
v<-1 ### fill all comb stock
for(i in d[[1]]) for(j in o[[2]]){
 cor.agg.fund.rf[v,4]<-cor.in.fund.res.mf[i,j]
 v<-v+1
}
for(i in d[[2]]) for(j in o[[1]]){
 cor.agg.fund.rf[v,4]<-cor.in.fund.res.mf[i,j]
 v<-v+1
}
v<-1 ### fill all comb bond
for(i in d[[1]]) for(j in o[[3]]){
 cor.agg.fund.rf[v,5]<-cor.in.fund.res.mf[i,j]
 v<-v+1
}
for(i in d[[3]]) for(j in o[[1]]){
 cor.agg.fund.rf[v,5]<-cor.in.fund.res.mf[i,j]
 v<-v+1
}
v<-1 ### fill all stock bond
for(i in d[[2]]) for(j in o[[3]]){
 cor.agg.fund.rf[v,6]<-cor.in.fund.res.mf[i,j]
 v<-v+1
}
for(i in d[[3]]) for(j in o[[2]]){
 cor.agg.fund.rf[v,5]<-cor.in.fund.res.mf[i,j]
 v<-v+1
}

cor.D<-cor.agg.D[rowSums(is.na(cor.agg.D)) != ncol(cor.agg.D),]
cor.rD<-cor.agg.rDf[rowSums(is.na(cor.agg.rDf)) != ncol(cor.agg.rDf),]

cor.O<-cor.agg.O[rowSums(is.na(cor.agg.O)) != ncol(cor.agg.O),]
cor.rO<-cor.agg.rOf[rowSums(is.na(cor.agg.rOf)) != ncol(cor.agg.rOf),]

cor.f<-cor.agg.fund[rowSums(is.na(cor.agg.fund)) != ncol(cor.agg.fund),]
cor.fr<-cor.agg.fund.rf[rowSums(is.na(cor.agg.fund.rf)) != ncol(cor.agg.fund.rf),]
#### testing correlation difference
month.agg<-rbind(cor.D, cor.O)
month.test<-matrix(NA, ncol=6, nrow=4)
colnames(month.test)<-c("comb-comb", "stock-stock", "bond-bond", "comb-stock", "comb-bond",
    "stock-bond")
rownames(month.test)<-c( "within family", "between family", "t-Stat", "p-Value")
for( i in 1:6) month.test[1,i]<-mean(month.agg[,i],na.rm=TRUE)
for( i in 1:6) month.test[2,i]<-mean(cor.f[,i],na.rm=TRUE)
for( i in 1:6){
 tt<-t.test(month.agg[,i], cor.f[,i], na.rm=TRUE, var.equal = FALSE)
 month.test[3,i]<-tt$statistic
 month.test[4,i]<-tt$p.value
}
View(month.test)

sample.mean<-matrix(NA, nrow=3, ncol=12)
```

```
colum.names<-c("in comb-comb", "in stock-stock", "in bond-bond", "in-comb-stock", "in-comb-
    bond", "in stock-bond", "out comb-comb", "out stock-stock", "out bond-bond" , "out comb-
    stock", "out comb-bond", "out stock-bond")
colnames(sample.mean)<-colum.names
row.names<-c( "total cor - ffm", "res cor - ffm", "syst cor - ffm" )
rownames(sample.mean)<-row.names

##### fill the correlation for funds
for( i in 1:6) sample.mean[1,i]<-mean(month.agg[,i],na.rm=TRUE)
for( i in 7:12) sample.mean[1,i]<-mean(cor.f[,i-6],na.rm=TRUE)
### Fill in residual correaltion
res.cor.mf<-rbind(cor.rD,cor.rO)
for( i in 1:6) sample.mean[2,i]<-mean(res.cor.mf[,i],na.rm=TRUE)
for( i in 7:12) sample.mean[2,i]<-mean(cor.fr[,i-6],na.rm=TRUE)
### fill in systematic correlation component
for(i in 1:12) sample.mean[3,i]<-sample.mean[2,i]-sample.mean[1,i]
View(sample.mean)

######### difference analysis for correlation
#### difference correlation for FFM
diff.corr.ffm<-matrix(NA, nrow=6, ncol=4)
colnames(diff.corr.ffm)<-c("Return correlation difference", "Systematic component
    difference", "Idiosyncratic component difference", "Ratio (3)/(1)")
rownames(diff.corr.ffm)<-c("comb-comb", "stock-stock", "bond-bond", "comb-stock", "comb-
    bond", "stock-bond")
for  (i in 0:5){diff.corr.ffm[i+1,1]<-sample.mean[1,i+1]-sample.mean[1,i+7]
diff.corr.ffm[i+1,2]<-sample.mean[3,i+1]-sample.mean[3,i+7]
diff.corr.ffm[i+1,3]<-sample.mean[2,i+1]-sample.mean[2,i+7]
diff.corr.ffm[i+1,4]<-abs(diff.corr.ffm[i+1,3]/diff.corr.ffm[i+1,1])}
View(diff.corr.ffm)

library(PerformanceAnalytics)
library(zoo)
###### Ranking upon Sharpe ratio
##For DNB
m2d<-matrix(NA, nrow=3, ncol=24)
colnames(m2d)<-colnames(DNB.m)
for(i in 1:24){
 m2d[1,i]<-mean(DNB.m[,i]-rft)
 m2d[2,i]<-sd(DNB.m[,i]-rft)
 m2d[3,i]<-m2d[1,i]*sd(SB.mt[,2])/m2d[2,i]+rft
}
md2<-rbind(m2d, rank(m2d[3,]),0)
for(i in 1:24) md2[5,i]<-md2[1,i]/md2[2,i]
md.2<-rbind(md2, rank(md2[5,]))
rownames(md.2)<-c("mean return", "sd", "M2", "rank by M2", "Sharpe ratio", "rank by S.r")
ranking.d<-t(md.2)
View(ranking.d)
## For ODIN
m2o<-matrix(NA, nrow=3, ncol=16)
colnames(m2o)<-colnames(ODIN.m)
for(i in 1:16){
 m2o[1,i]<-mean(ODIN.m[,i]-rft)
 m2o[2,i]<-sd(ODIN.m[,i]-rft)
 m2o[3,i]<-m2o[1,i]*sd(SB.mt[,2])/m2o[2,i]+rft
}
mo2<-rbind(m2o, rank(m2o[3,]),0)
for(i in 1:16) mo2[5,i]<-mo2[1,i]/mo2[2,i]
mo.2<-rbind(mo2, rank(mo2[5,]))
rownames(mo.2)<-c("mean return", "sd", "M2", "rank by M2", "Sharpe ratio", "rank by S.r")
ranking.o<-t(mo.2)
View(ranking.o)

###### portfolio optimization - tangency portfolio
library(fPortfolio)
```

```
spec<-portfolioSpec()
setOptimize(spec)<-"minRisk"
setSolver(spec)<-"solveRquadprog"
setNFrontierPoints(spec) <-1000
constraints<-"LongOnly"
setRiskFreeRate(spec)<-rft
spec1<-spec
setNFrontierPoints(spec1)<-(15)
##### For DNB - optimal
dnb.port1<-matrix(NA, ncol=9, nrow=length(d[[2]])*length(d[[3]]))

colnames(dnb.port1)=c("stock #", "bond #", "w stock", "w bond", "mu", "sigma", "Sharpe",
    "M2", "cov")
v<-1
for(i in d[[2]]) for(j in d[[3]]){
 data.tang<-cbind(DNB.m[,i],DNB.m[,j])
 dnb.tang<-tangencyPortfolio(as.timeSeries(data.tang), spec, constraints)
 dnb.port1[v,1]<-i
 dnb.port1[v,2]<-j
 dnb.port1[v,3]<- getWeights(dnb.tang)[1]
 dnb.port1[v,4]<- getWeights(dnb.tang)[2]
 dnb.port1[v,5]<- getTargetReturn(dnb.tang)[1]
 dnb.port1[v,6]<- getTargetRisk(dnb.tang)[2]
 dnb.port1[v,7]<- (dnb.port1[v,5]-rft)/dnb.port1[v,6]
 dnb.port1[v,8]<- dnb.port1[v,7]*sd(SB.mt[,2])+rft
 dnb.port1[v,9]<-cov(DNB.m[,i],DNB.m[,j])
 v<-v+1
}
View(dnb.port1)

##### for ODIN
odin.port1<-matrix(NA, ncol=9, nrow=length(o[[2]])*length(o[[3]]))
colnames(odin.port1)=c("stock #", "bond #", "w stock", "w bond", "mu", "sigma", "Sharpe",
    "M2", "cov")
v<-1
for(i in o[[2]]) for(j in o[[3]]){
 data.tang<-cbind(ODIN.m[,i],ODIN.m[,j])
 odin.tang<-tangencyPortfolio(as.timeSeries(data.tang), spec, constraints)
 odin.port1[v,1]<-i
 odin.port1[v,2]<-j
 odin.port1[v,3]<- getWeights(odin.tang)[1]
 odin.port1[v,4]<- getWeights(odin.tang)[2]
 odin.port1[v,5]<- getTargetReturn(odin.tang)[1]
 odin.port1[v,6]<- getTargetRisk(odin.tang)[2]
 odin.port1[v,7]<- (odin.port1[v,5]-rft)/odin.port1[v,6]
 odin.port1[v,8]<- odin.port1[v,7]*sd(SB.mt[,2])+rft
 odin.port1[v,9]<- cov(ODIN.m[,i],ODIN.m[,j])
 v<-v+1
}
View(odin.port1)

#### for mixed family portfolio
mix.port1<-matrix(NA, ncol=9,
    nrow=(length(d[[2]])*length(o[[3]])+length(o[[2]])*length(d[[3]])+1))
colnames(mix.port1)=c("stock #", "bond #", "w stock", "w bond", "mu", "sigma", "Sharpe",
    "M2","cov")
v<-1
for(i in d[[2]]) for(j in o[[3]]){
 data.tang<-cbind(DNB.m[,i],ODIN.m[,j])
 mix.tang<-tangencyPortfolio(as.timeSeries(data.tang), spec, constraints)
 mix.port1[v,1]<-i
 mix.port1[v,2]<-j
 mix.port1[v,3]<- getWeights(mix.tang)[1]
 mix.port1[v,4]<- getWeights(mix.tang)[2]
```

```
 mix.port1[v,5]<- getTargetReturn(mix.tang)[1]
 mix.port1[v,6]<- getTargetRisk(mix.tang)[2]
 mix.port1[v,7]<- (mix.port1[v,5]-rft)/mix.port1[v,6]
 mix.port1[v,8]<- mix.port1[v,7]*sd(SB.mt[,2])+rft
 mix.port1[v,9]<- cov(DNB.m[,i],ODIN.m[,j])
 v<-v+1
}
v<-v+1
for(i in o[[2]]) for(j in d[[3]]){
 data.tang<-cbind(ODIN.m[,i],DNB.m[,j])
 mix.tang<-tangencyPortfolio(as.timeSeries(data.tang), spec, constraints)
 mix.port1[v,1]<-i
 mix.port1[v,2]<-j
 mix.port1[v,3]<- getWeights(mix.tang)[1]
 mix.port1[v,4]<- getWeights(mix.tang)[2]
 mix.port1[v,5]<- getTargetReturn(mix.tang)[1]
 mix.port1[v,6]<- getTargetRisk(mix.tang)[2]
 mix.port1[v,7]<- (mix.port1[v,5]-rft)/mix.port1[v,6]
 mix.port1[v,8]<- mix.port1[v,7]*sd(SB.mt[,2])+rft
 mix.port1[v,9]<- cov(DNB.m[,j],ODIN.m[,i])
 v<-v+1
}
View(mix.port1)

#### generating stock-bond data set
## For DNB
data.d<-DNB.m[, !colnames(DNB.m) %in% c("da10", "da100", "da30", "da50", "da80","dlik4")]
names(data.d)<-colnames(data.d)
##### For ODIN
data.o<-ODIN.m[, !colnames(ODIN.m) %in% c("flex", "horizt", "okons")]
names(data.o)<-colnames(data.o)
### For mixed fund portfolio
data.f<-cbind(data.d,data.o)
names(data.f)<-colnames(data.f)
### creation of summary table
mix.p<-matrix(NA, ncol=6, nrow=3) # table for tangency portfolio summary
colnames(mix.p)<-c("Stock", "Bond", "Mu", "Sigma","Sharpe", "M2")
rownames(mix.p)<-c("From DNB ", "From ODIN", "Mixed")

# redefine amount of portfolio in order to insert them into Appendices
frontier.d<-portfolioFrontier(as.timeSeries(data.d), spec, constraints) # efficient frontier
    for DNB
tangen.d<-tangencyPortfolio(as.timeSeries(data.d), spec, constraints)  # minimize risk

frontier.o<-portfolioFrontier(as.timeSeries(data.o), spec, constraints) # efficient frontier
    for ODIN
tangen.o<-tangencyPortfolio(as.timeSeries(data.o), spec, constraints)  # minimize risk

frontier.f<-portfolioFrontier(as.timeSeries(data.f), spec, constraints) # efficient frontier
    for fundstangen.f<-tangencyPortfolio(as.timeSeries(data.f))
tangen.f<-tangencyPortfolio(as.timeSeries(data.f), spec, constraints)  # minimize risk
#### Adding main parameters of the portfolio in summary table
Sh.d<-(getTargetReturn(tangen.d)[1]-rft)/getTargetRisk(tangen.d)[2]
mix.p[1,5]<-Sh.d
M2.d<-Sh.d*sd(SB.mt[,2])+rft
mix.p[1,6]<-M2.d
mix.p[1,3]<-getTargetReturn(tangen.d)[1]
mix.p[1,4]<-getTargetRisk(tangen.d)[2]

Sh.o<-(getTargetReturn(tangen.o)[1]-rft)/getTargetRisk(tangen.o)[2]
mix.p[2,5]<-Sh.o
M2.o<-Sh.o*sd(SB.mt[,2])+rft
mix.p[2,6]<-M2.o
mix.p[2,3]<-getTargetReturn(tangen.o)[1]
mix.p[2,4]<-getTargetRisk(tangen.o)[2]
```

```
Sh.f<-(getTargetReturn(tangen.f)[1]-rft)/getTargetRisk(tangen.f)[2]
mix.p[3,5]<-Sh.f
M2.f<-Sh.f*sd(SB.mt[,2])+rft
mix.p[3,6]<-M2.f
mix.p[3,3]<-getTargetReturn(tangen.f)[1]
mix.p[3,4]<-getTargetRisk(tangen.f)[2]
### Plotting preparations
d.points<-frontierPoints(frontier.d)
o.points<-frontierPoints(frontier.o)
f.points<-frontierPoints(frontier.f)
axe.x<-range(0.0015, 0.006)
axe.y<-range(-0.0005, 0.006)
# Plot for DNB frontier
graphics.off()
plot(d.points, pch=16, col="seagreen1", ylim=range(0.001, 0.009), xlim=range(0.003, 0.009))
tangencyPoints(tangen.d, return = c("mean"), risk = c( "Sigma"), auto = TRUE, col="blue", pch
    = 19)
tangencyLines(tangen.d, col="darkgreen")
abline(h = getTargetReturn(tangen.d), col = "grey")
abline(v = getTargetRisk(tangen.d)[2], col = "grey")
text(0.0031,getTargetReturn(tangen.d), labels=as.character(
    round(getTargetReturn(tangen.d)[1], digits=4)))
text(getTargetRisk(tangen.d)[2],0.001, labels=as.character(round(getTargetRisk(tangen.d)[2],
    digits=4)))
legend("topleft", legend=c("DNB efficient frontier", "Tangency portfolio"),
    col=c("seagreen1", "blue"), pch=16)
# Plot for ODIN frontier
graphics.off()
plot(o.points, col="plum2", pch=16, ylim=axe.y, xlim=axe.x)
tangencyPoints(tangen.o, return = c("mean"), risk = c( "Sigma"), auto = TRUE, col="red3", pch
    = 19)
tangencyLines(tangen.o, col="darkblue")
abline(h = getTargetReturn(tangen.o), col = "grey")
abline(v = getTargetRisk(tangen.o)[2], col = "grey")
text(0.0016,getTargetReturn(tangen.o), labels=as.character(
    round(getTargetReturn(tangen.o)[1], digits=4)))
text(getTargetRisk(tangen.o)[2],0, labels=as.character(round(getTargetRisk(tangen.o)[2],
    digits=4)))
legend("topleft", legend=c("ODIN efficient frontier", "Tangency portfolio"), col=c("plum2",
    "red3"), pch=16)
# Plot for mixed portfoio frontier
graphics.off()
plot(f.points, col="mediumorchid1", pch=16, ylim=axe.y, xlim=axe.x)
tangencyPoints(tangen.f, return = c("mean"), risk = c( "Sigma"), auto = TRUE, col="black",
    pch = 19, cex=1.5)
tangencyLines(tangen.f, col="darkgreen", lwd=1.7)
abline(h = getTargetReturn(tangen.f), col = "grey")
abline(v = getTargetRisk(tangen.f)[2], col = "grey")
text(0.0016,getTargetReturn(tangen.f), labels=as.character(
    round(getTargetReturn(tangen.f)[1], digits=4)))
text(getTargetRisk(tangen.f)[2],0, labels=as.character(round(getTargetRisk(tangen.f)[2],
    digits=4)))
legend("topleft", legend=c("Mixed efficient frontier", "Tangency portfolio"),
    col=c("mediumorchid1", "black"), pch=16)


##### compute weights of stocks and bond
### for DNB
mix.p[1,1]<-0
for(j in 1:15) mix.p[1,1]<-mix.p[1,1]+getWeights(tangen.d)[j]
mix.p[1,2]<-1-mix.p[1,1]
#### for ODIN
mix.p[2,1]<-0
for(i in 1:10) mix.p[2,1]<-mix.p[2,1]+getWeights(tangen.o)[i]
```

```
mix.p[2,2]<-1-mix.p[2,1]

### For mixed portfolio
mix.p[3,1]<-0
for(i in 1:15) mix.p[3,1]<-mix.p[3,1]+getWeights(tangen.f)[i]
for(i in 19:28) mix.p[3,1]<-mix.p[3,1]+getWeights(tangen.f)[i]
mix.p[3,2]<-1-mix.p[3,1]
View(mix.p) # shows tangency portfolio statistics

### print out summary of the function
getPortfolio(portfolioFrontier(as.timeSeries(data.d), spec1, constraints))
getPortfolio(portfolioFrontier(as.timeSeries(data.o), spec1, constraints))
getPortfolio(portfolioFrontier(as.timeSeries(data.f), spec1, constraints))

print(tangen.d)
print(tangen.o)
print(tangen.f)
```