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Equity Share and the Downside Risk at the Norwegian
Government Pension Fund Global (GPF-G)

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**Equity Share and the Downside Risk at the Norwegian
Government Pension Fund Global (GPF-G)**

Master Thesis

by

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MSc in Finance

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The school takes no responsibility for the methods used, results found, or

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Contents

1	Introduction	1
2	Background and Literature	5
2.1	Sharpe Ratio	7
2.2	Drawdown	8
2.3	Semivariance	8
2.4	Skewness and Kurtosis	9
3	Theory and Hypotheses	10
4	Methodology	10
4.1	Simulation	10
4.2	Bootstrapping	11
4.2.1	Bootstrapping vs. other statistical methods	12
4.2.2	The Central Limit Theorem (CLT)	12
4.3	Performing Evaluation	13
4.4	Terminal Value Analysis	16
4.4.1	Empirical Cumulative Distribution Function (ECDF)	16
4.4.2	Excessive Downside Risk	17
5	Data	17

6 Empirical analysis	18
6.1 Asset Allocation	19
6.1.1 Tail Analysis	19
6.1.2 Currency Analysis	25
6.1.3 Fund Sustainability Analysis	27
6.2 Equity Share	29
6.2.1 Tail Analysis	31
7 Conclusion	35
7.1 Key Findings and Implications	35
7.2 Limitations and Guidelines for Future Research	37
8 Bibliography	39
9 Appendix	44

List of Figures

Figure 1	Empirical Cumulative Density Function (ECDF)	30
Figure 2	Summary of Variables	44
Figure 3	Backtesting Asset Allocation	45
Figure 4	Backtesting Equity Allocation	45

List of Tables

Table 1	Asset Allocation at the GPF-G	14
Table 2	Changes in Equity Allocation at the GPF-G	14
Table 3	Expected Nominal Returns summary statistics	26
Table 4	Drawdown % summary statistics	27
Table 5	Terminal Value (TV) Distribution	28
Table 6	Basket Returns' Calculation Methodology	46
Table 7	Market Size weights' Calculation Methodology	47
Table 8	Nominal Returns summary statistics (Asset Allocation)	48
Table 9	Standard Deviation summary statistics (Asset Allocation)	49
Table 10	Sharpe Ratio summary statistics (Asset Allocation)	50
Table 11	Drawdown % summary statistics (Asset Allocation)	51
Table 12	Drawdown time summary statistics (Asset Allocation)	52

Table 13	Semivariance summary statistics (Asset Allocation)	53
Table 14	Excess Kurtosis summary statistics (Asset Allocation)	54
Table 15	Skewness summary statistics (Asset Allocation)	55
Table 16	Terminal Value summary statistics (Asset Allocation)	56
Table 17	Expected Nominal Returns summary statistics (Equity Share)	57
Table 18	Standard Deviation summary statistics (Equity Share)	58
Table 19	Sharpe Ratio summary statistics (Equity Share)	59
Table 20	Drawdown % summary statistics (Equity Share)	60
Table 21	Drawdown Time summary statistics (Equity Share)	61
Table 22	Semivariance summary statistics (Equity Share)	62
Table 23	Excess Kurtosis summary statistics (Equity Share)	63
Table 24	Skewness summary statistics (Equity Share)	64
Table 25	FTSE Markets Classification	65
Table 26	Comparison Z-scores Asset Allocation	66
Table 27	Comparison Z-scores Asset Allocation (continued)	67
Table 28	Comparison Z-scores Equity Share	68
Table 29	Comparison Z-scores Equity Share (continued)	69

Abstract

This paper studies the changes in asset and equity allocations across asset classes and markets in the Norwegian Government Pension Fund Global's (GPF-G or "The Fund") portfolio. It evaluates how the shifts in the investment mandate, primarily the increase in equity investments since The Fund's creation, have affected downside risk. We aim to assess changes across time and individual risk and set the basis for a global view on the fund's downside risk.

1 Introduction

Traditionally, researchers have evaluated changes in asset allocation by comparing expected return gains to increases in expected portfolio volatility. However, little attention has been paid to the role of downside risk. This thesis aims to evaluate changes in allocation across asset classes and the exposure to markets in the Portfolio of the Norwegian Government Pension Fund (GPF-G or "The Fund"). More specifically, we consider the increase in equity investments since its inception and its ramifications.

The GPF-G is a Sovereign Wealth Fund (SWF) sourced from oil revenues created to perform an oil to equity transformation, and which has three main policy goals: 1) to act as a buffer to smooth short term variations in the oil revenues; 2) to serve as a tool for coping with an aging population and the eventual decline in oil revenues, and 3) to be an equitable form of transferring of wealth to future generations. In other words, we can understand this transformation as converting oil barrels into financial assets by acquiring small stakes in all easily traded companies in signifi-

cant markets (Norges Bank Investment Management, 2021).

As the world's largest Sovereign Wealth Fund, it greatly influences the Norwegian economy and society. Therefore, understanding how The Fund can affect the welfare of current and future generations is one of the main motivations for writing this paper. Also, there is a scientific reason why this is an interesting question, both from a sustainability and a portfolio management perspectives: our main focus in this paper is to look at the NBIM and the GPF-G's sustainability over the long run as it is an important institution for the Norwegian economy. Sustainability is an issue that arises in all institutions globally (e.g., universities), and is, therefore, a paramount issue worth being studied.

To put things into perspective, we also consider Harvard's Endowment and Denmark's ATP pension fund. We highlight their similarities and differences with the GPF-G and establish why the sustainability issue would be of great importance for these other institutions. Harvard's Endowment is a trust that has existed for nearly four centuries. It belongs to the current and future generations of students, faculty, and researchers. Like The Fund, Harvard's Endowment is structured to exist in perpetuity—the institution must continue to rely on the Endowment's earnings forever. Therefore, it is carefully managed to ensure that future generations will enjoy its benefits as much as the current ones. It comprises 14,000+ individual funds invested as a single entity, and its returns have enabled leading financial aid programs and groundbreaking research. A portion of the Endowment is paid out annually as distribution to support the University's budget, and any excess is retained in the Endowment so it can grow and support future generations. Distributions from Har-

vard's Endowment provide a critical source of funding for the University. The Endowment distributed USD 2 billion in the fiscal year ending June 30, 2020, contributing over a third of Harvard's total operating revenue in that year (Harvard, 2021).

Arbejdsmarkedets Tillægspension (ATP) is Denmark's largest pension fund and processing business. The Danish Parliament established it in 1964 to ensure basic financial security in Denmark and a stable and guaranteed pension for both current and future generations (Lifelong pension). Via responsible investments, ATP pays welfare and social security benefits amounting to around DKK 300 billion (USD 50 billion) per year, corresponding to around two out of every three Danish kroner in welfare spending.

Different from The Fund, ATP was founded to ensure basic financial security to Danes throughout their lives. It does so by administering welfare state pension benefits such as holiday pay, maternity/paternity pay, and rent subsidies. ATP adopts an approach very focused on investing Danish individuals' savings. However, its overarching objective is very similar to one of The Fund's objectives: to ensure that both current and future generations receive lifelong benefits.

Investors care differently about downside losses and upside gains. Markowitz (1959) advocated utilizing semivariance as a risk measure instead of variance, once the former weighs downside losses in a different way that it measures upside gains. Thus, downside risk refers to the probability that an asset or portfolio will experience a price decline. In other words, it is the potential loss resulting from a

decrease in price due to changes in market conditions. Downside risk is vital for the Fund and Norwegians because emphasizing potential downside losses helps calibrate risk tolerances. It allows for decision-making based on an appropriate amount of factor exposure and affects how the fund can contribute over the long term to the Norwegian budget. Past experiences have shown that financial products can be unpredictable in times of distress: volatility and correlation between asset classes increase. It can catch investors off-guard and cause considerable losses and catastrophic events.

Initially wholly invested in government bonds, The Fund had 40% of its portfolio converted into equities by mid-1998, a share increased to 60% by 2007. In 2018, it included real estate in the portfolio, whose allocation was sized to up to 5%. In 2019, The Fund reached a portfolio value of NOK 10 trillion. Under its current allocation, about 70% of The Fund is invested in equities, 30% in Fixed Income, and up to 7% and 2% can be invested in unlisted real estate and renewable energy infrastructure, respectively. It is essential to mention the change in the composition of the equity portfolio of the GPF-G. The inclusion of Emerging Markets and Frontier Markets in addition to a portfolio initially invested in only Developed Markets are changes that would increase the riskiness of the equity share of the portfolio (refer to Figures 3 and 4 for backtesting of both asset and equity allocations). Also worth highlighting is the importance of capturing the effect of downside risk when analyzing the changes that have been applied to The Fund's composition. Throughout the past 30 years—especially after the 2008-2009 financial crisis, it became clear that part of the Fund's performance was attributable to risk factors other than beta risk.

This paper aims to conduct simulations to construct portfolios used to evaluate the future excessive downside risk of alternative allocations. It will also investigate whether gains in returns from increased equity allocation do not come at the cost of considerably higher downside risk. We see downside risk affecting how The Fund can contribute over the long term to the Norwegian Budget. Therefore, our research aims to simulate future states of the GPF-G to gain insights from the changes in asset allocations, analyze the inclusion of Emerging and Frontier markets into the equity share, and evaluate The Fund's future sustainability.

2 Background and Literature

The role of the GPF-G goes beyond being a vehicle for storing wealth from oil activities for future generations. The fund has an embedded role by design in the decision-making and financial planning for the Norwegian economy by governmental parties such as the Ministry of Finance and Stortinget (The Norwegian Parliament). The legal framework that regulates the revenues to the state from oil activities is the *Handlingsregelen*, referred to in English as *The Budgetary Rule*. The annual transfer to the budget is limited to up to 3% of the GPF-G's end-of-the-year value. It is intuitive now to infer the ramifications of downside risk. It is not limited to the net worth of the fund at any given time, but the role it might play on the budget flexibility during times of economic distress. The mandate of this rule is to maintain in the long run the equality between government expenditure and government revenues, apart from the mainland economy and the expected future real return from the GPF-G.

The Ministry of Finance has, under the Government Pension Fund Act, been given the formal responsibility for the management of the Fund, divided into GPF-G and the Government Pension Fund Norway (GPF-N). However, the operational management of GPF-G is carried out by Norges Bank Investment Management (NBIM). NBIM has adopted a limited active investment philosophy that focuses on assessing fundamental value (i.e., identifying mispriced assets). Active management can be defined as taking positions that differ from the market-weighted bond or stock portfolios. NBIM's approach included tactical asset allocation, factor-based position-taking, relative value, and fundamental value strategies. Empirical evidence shows active strategies account only for a small part of The Fund's overall performance. A manager should seek to maximize the return of a portfolio relative to that of the benchmark, or, in other words, try to obtain the highest alpha possible (Ang, A., Goetzmann, W., Schaefer, S., 2009). In evaluating The Fund's track record, they find that "active management has played a minimal role in its performance to date. The Incremental contribution of active management has been slightly positive overall [...]". (Norwegian Ministry of Finance, 2019-2020).

In the early days, the GPF-G relied on the Capital Asset Pricing Model (CAPM), a simple asset-based approach account. The only priced risk factor is the beta coefficient of an asset. However, this has significantly changed, and research has found that the beta of a single-factor CAPM is a statistic that fails to account for risk accurately. It only accounts for the market risk premium. It does not capture the asymmetry between upside and downside risks, especially the latter's importance when analyzing losses in "bad times." The most commonly used approach used in

recent times is a multi-factor model called Arbitrage Pricing Theory (APT). Under APT, the investor should be compensated by higher returns when accepting the risk implied by their exposure to risk factors. One limitation of this model is that one needs to identify all the risk factors for each security. Failing to identify a factor would run the risk of measurement error. Moreover, there is a risk of correlation between factors that would produce noisy estimators.

The downside risk is a method to gauge risk that identifies returns below a specified benchmark return level (i.e., something bad happens) (Harlow, 1991; Berg and Starp, 2006). Earlier, Markowitz (1952) proposed using semivariance as a more efficient method of quantifying risk by focusing on the downside of returns. More extensively, Ang, A., Chen, and J., Xing, Y., (2016, p. 1192) suggest that downside risk might carry a premium with which agents are compensated. It opens the doors for exploring sources of returns according to the risk profile of The Fund.

In order to bring more perspective into our literature review, we proceed with introducing measures for quantifying portfolios' risk and return profiles.

2.1 Sharpe Ratio

The reward-to-variability ratio (more commonly known as the Sharpe ratio (SR)) was introduced by William Sharpe (Sharpe, 1966). It measures volatility-adjusted performance that defines the excess return (asset or portfolio return minus risk-free rate return) divided by the asset and portfolio's standard deviation of returns. The SR adjusts a portfolio's performance for the excess risk taken by an investor, and preferably, the higher the SR, the better. However, the Sharpe ratio presents weak-

nesses, including the assumption that investment returns are normally distributed.

2.2 Drawdown

Another relevant measure of risk that can be considered when assessing the downside risk of pension funds is the Drawdown. The maximum loss from a market peak to a market nadir, commonly called the maximum drawdown (MDD), measures how sustained one's losses can be (Magdon-Ismail and Atiya, 2004). For instance, we can use Maximum Drawdown (MDD) to measure the maximum cumulative loss experienced by a portfolio over its history.

2.3 Semivariance

According to Boasson et al. (2011), using variance as a measure for downside risk is only appropriate if returns are normally distributed; this property does not hold in practice. Variance as a measure of risk captures both the upside and downside movements (Fishburn, 1977). This research paper is interested in the returns below a certain level for the GPF-G. For this, semivariance as a measure of downside risk better adjusts to our study. It is defined as the weighted sum of square deviations from a certain threshold considering only those values below the expected value of returns (Ballester, 2005). Markowitz (1991) discussed that semivariance as a measure of risk is a better solution than what the mean-variance theory might suggest.

2.4 Skewness and Kurtosis

During the late 19th century, any frequency distribution was considered—by statisticians—to follow a normal distribution. Karl Pearson (1916) was the one to propose a system of theoretical curves with a wide variety of shapes to provide more accurate representations of observed data. The classification of distributions inside the Pearson system was entirely determined by the two moment ratios: skewness and kurtosis.

The interpretation of skewness was relatively "transparent" and intuitive, but significant difficulties arose with the understanding of kurtosis. (...) Curves with kurtosis values less than three (3) are flat-topped compared to a normal distribution and called platykurtic. Curves with values greater than three (3) are peaked more sharply and called leptokurtic (Yule & Kendall's, 1937).

The downside risk is relevant only when the distribution of security returns is skewed. Skewness refers to the asymmetry that deviates from the symmetrical bell curve in a data set; it is the extent to which a given distribution varies from a normal distribution. When the skewness of an asset or a portfolio's return distribution is negative, downside returns tend to be larger than upside returns. On the other hand, when the skewness of the security returns distribution is positive, upside returns will have a larger magnitude than the downside returns. Along with skewness, kurtosis is a critical, descriptive statistic of data distribution. Kurtosis defines how heavily the tails of a distribution differ from the tails of a normal distribution or whether the tails of a given distribution contain extreme values. Positive excess kurtosis indicates fatter tails than a normal distribution, i.e., a higher frequency of

extreme returns than normal distribution. In comparison, negative kurtosis indicates thinner tails than that of a normal distribution. However, according to Post and Vliet (2006), the downside risk is not fully captured by skewness and kurtosis.

For more information on the metrics discussed above, refer to Figure 2 in the appendix.

3 Theory and Hypotheses

The equity share in the portfolio allocation has been increasing from 40% in 1998 to up to 70% in 2021. In addition, the equity share has shifted from 100% in Developed Markets to a progressive inclusion of Emerging and Frontier markets. We hypothesize that the increase of the equity share in the portfolio and the shift into Emerging and Frontier markets can be translated into an increase in both expected returns and risk. It is a trade-off that needs to reflect the risk of loss of wealth, the level of overall risk in the nation's total wealth, and the fiscal policy rate of The Fund (Mork, 2016). Changes in asset allocation and equity share throughout the years have come at the expense of increased downside risk, and, with this paper, we aim to quantify it and define whether it is excessive or not.

4 Methodology

4.1 Simulation

In this paper, we conduct simulations based on the data from The Fund's inception until the present. Simulation refers to a procedure that predicts risk by 'simulating'

asset returns over time. In this case, we use the whole sample in every simulation given 23 years of data (1998-2021) to simulate returns for each asset allocation and the equity share through proxy returns. The simulations will be carried out using bootstrapping with replacement, which we describe in the following paragraphs.

4.2 Bootstrapping

The basic idea of bootstrapping is that inference about a population from sample data (population \rightarrow sample) can be modeled by resampling the sample data and performing inference about a sample from resampled data (resampled \rightarrow sample) (Cline, G. 2019). As the population cannot be observed and is unknown, the true error in a sample is also unknown. In bootstrap resamples, the population is the sample, and the sample is known. Therefore, it is possible to measure the quality of the inference of the “true” sample from resampled data. In other words, it is a method that estimates the sampling distribution by taking multiple samples with replacement from a single random sample. These repeated samples are called resamples—in this specific case, the resamples are our simulations into the future. It is noteworthy that increasing the number of resamples is not supposed to increase the amount of information in the data; this is dependent on the sample size, n , which will remain constant throughout each resample. The benefit of more resamples is to derive a better estimate of the sampling distribution (Mooney & Duval, 1993).

Bootstrapping with replacement is a form of resampling in which each resample can have some of the original data points presented more than once and some which are not represented at all. Therefore, each of these resamples will likely be slightly

and randomly different from the original sample. We choose to resample with replacement over without replacement as otherwise, it would be a mere reordering of the values.

4.2.1 Bootstrapping vs. other statistical methods

An outstanding advantage of bootstrapping is its simplicity. Straightforwardly, it derives estimates of standard errors and confidence intervals for complex estimators of complex parameters of the distribution. It is also a way to control and check the stability of the results. For most problems, it is not possible to know the “true” confidence intervals. Bootstrap is asymptotically more accurate than the standard intervals obtained using sample variance and assumptions of normality (Cline, G. 2019). With bootstrap, there is no need to make any assumptions regarding the data distribution, which contrasts with the traditional approach, which theoretically assumes the data is normally distributed.

4.2.2 The Central Limit Theorem (CLT)

The Central Limit Theorem (CLT) is a critical component of hypothesis testing. It is considered to be one of the most important theorems in statistics. Without it, parametric tests would not be regarded as accurate tools for estimating population dynamics (Howell, 2002). The CLT states that the distribution of a sample approximates that of a normal distribution as the sample size becomes larger. It also assumes that all samples are identical in size n , and regardless of the population distribution shape.

When performing bootstrapping with replacement on a data sample, we treat it as if

it is the whole population. We draw many “resamples” of the original sample with size n , both random and with replacement, through a Monte Carlo simulation. As a consequence, each of the resamples will have slightly different statistics, means included (Mooney and Duval, 1993). Therefore, we turn our attention to the ranges of distribution values as opposed to single estimates.

4.3 Performing Evaluation

In order to determine the downside risk of the GPF-G, we conduct a two-dimensional analysis, while adopting a top-down approach. First, we consider the portfolio asset allocations, using The Fund’s weights since its inception in 1998, as shown in Table 1. Then, considering that the equity portfolio composition has changed throughout time, we perform a similar analysis for the equity share and compute the respective weights for each of the markets under study (Developed, Emerging, and Frontier), as seen in Table 2. Refer to Table 7 in the appendix for further information on the weights’ calculation.

For both dimensions, our study seeks to measure if the different states of the Fund would lead to an excessive increase in the portfolio’s downside risk into the future. Firstly, we run simulations with 10,000 iterations to forecast the performance for each state using the whole sample data as explained in the section above. Secondly, we construct portfolios using the respective weights for portfolio asset allocation and equity share changes (recall Tables 1 and 2). Third, we perform analyses on the summary statistics for each of the measures utilized in this paper to quantify and measure downside risk and fund sustainability, in the Asset Allocation case.

Table 1: Asset Allocation at the GPF-G

Year	Equities	Fixed Income	Real Estate
1998	40%	60%	-
2007	60%	40%	-
2008	≤ 60%	≤ 40%	≤ 5%
2010	≤ 60%	≤ 35%	≤ 5%
2017	≤ 60%	≤ 33%	≤ 7%
2020-Present	≤ 70%	≤ 30%	≤ 7%

Source: Norges Bank

Table 2: Changes in Equity Allocation at the GPF-G

Year	Developed Markets	Emerging Markets	Frontier Markets
1998-2007	100.00%	0.00%	0.00%
2007-2008	95.25%	4.72%	0.00%
2008-2010	93.19%	6.77%	0.00%
2010-2017	89.46%	10.50%	0.00%
2017-2020	88.96%	10.81%	0.00%
2020-Present	87.71%	12.11%	0.00%

Source: The weights of this table were computed using Norges Bank data for individual country investments.

For the equity share, since Norges Bank does not disclose monthly returns segmented into the markets mentioned above, we use proxy returns based on FTSE indexes for the respective markets. These figures are only available in USD and NOK. We transform USD returns into basket returns. Refer to Table 6 in the Appendix for calculations used to derive the Basket-currency returns. Furthermore, to have a more accurate representation of the proxy returns, we exclude Norway's proportional returns from the FTSE Developed Index as The Fund cannot invest in the country per its mandate. Given data limitations, we assume Norway's weight

(0.20%) in the index to be constant to remove Norway's contribution to the index across the sample period.

We construct three sets of analyses for evaluating the portfolio's asset allocation; however, we only consider the two first when assessing the equity share of the portfolio. The first set examines downside risk from a nominal returns perspective from the constructed simulations—ignoring the effect of currencies, inflation, and withdrawals. The second step examines whether reporting funds performance in Norwegian Krone, US dollars, or a basket of currencies affects the measure of downside risk. In the third set of analyses, we account for expected inflation and withdrawals to measure The Fund's future sustainability, given each asset allocation under examination.

While we report the different metrics of downside risk throughout our study, our main discussion in the Asset Allocation segment of this thesis focuses on The Fund's terminal value relative to its strategic value, which in turn is a primary measure of sustainability. The section *Fund Sustainability Analysis* which mainly assesses the terminal value of the portfolio, derives its motivation from the fact that just evaluating the metrics used to quantify risk is not sufficient to determine whether The Fund will meet its mandate. The mandate includes ensuring responsible and long-term management of revenue from Norway's oil and gas resources so that this wealth benefits both current and future generations (Norges Bank Investment Management, 2021).

This paper refers to NOK as the 'spending currency' used to transfer funds from

The Fund into the government's budget. Similarly, we refer to USD and basket as the 'investing currencies'—currencies used for investing purposes. It is important to remember that The Fund receives inflows in NOK; nonetheless, all investments are carried out outside of Norway, according to its mandate.

4.4 Terminal Value Analysis

To measure sustainability, we perform a terminal value (TV) analysis. We define a sustainable fund as one that can grow in real terms; net of expected inflation and withdrawals (positive TV factor). We modeled the terminal values—for the coming 25 years—estimating global average inflation at 3.42% (three-years average from 2018-2020). Then, we accounted for the Budgetary Rule—oil revenues transferred yearly to the state's budget—to cover the deficits and smooth out any fluctuations in the Norwegian economy. This rule stipulates a maximum withdrawal of 3% of the fund's value any given year. Lastly, we compute the cumulative return across all simulations to get a single TV factor number. For instance, a 'cumulative TV factor' of 23% would indicate that the fund is expected to grow 23%, from 2020's end-of-the-year value, in real terms after accounting for inflation and maximum withdrawals (Budgetary Rule) in the next 25 years (2021-2046).

4.4.1 Empirical Cumulative Distribution Function (ECDF)

We can translate cumulative Distribution Functions into probabilities that accumulate as we move from left to right along the x-axis in a probability distribution. "Empirical" only means we are concerned with observations rather than theory. A plot of an ECDF shows the estimated probability that the area of a sample is less

than or equal to a specific value and returns a function of the cumulative probability (University of Virginia, 2020).

4.4.2 Excessive Downside Risk

We utilize the ECDF to estimate the probability that any asset allocation (recall Table 1) will have an increased probability that The Fund's value would shirk in real terms. The riskiness of the simulated portfolio is measured in the three currencies Norges Bank Investment Management uses for reporting purposes—NOK, USD, and basket. Moreover, we consider excessive downside risk any allocation that would fail to have an expected positive TV factor in the three reporting currencies and decrease the value of the fund in real terms. Thus, this would affect The Fund's purchasing power in both in spending currency (NOK) and investing currencies (USD and basket).

5 Data

Our research strategy is divided into two components: 1) the changes in asset allocations, and 2) the changes in the equity share divided by markets (i.e., Developed Markets, Emerging Markets, and Frontier Markets). For the first component, we retrieve data from Norges Bank regarding the universe of historical results held by the fund. We use the portfolio's return and the return for each asset class (equity, fixed income, and real estate) reported in USD, NOK, and basket currencies. The data provided by Norges Bank is available with a monthly frequency ranging from 1998 to 2020. We obtain the budgetary rule's target of 3% from the Ministry of Finance (Regjeringen) and global inflation from The World Bank's database. For

the second component, we use the following indices provided by FTSE: FTSE Developed Index (FTAD01), FTSE Emerging Index (FTAG01), and FTSE Frontier 50 Index (FF50). Moreover, in order to exclude Norway from the index as The Fund cannot invest within the country, we gathered historical monthly returns data for the FTSE Norway Index (FTC2NO) and collected Norway's weight in the index from FTSE Developed Index 2020 factsheet (FTSE Russel, 2021). The proxy indexes data retrieved from Bloomberg is available in a monthly frequency, and ranges from 1993-2021. We download spreadsheets containing equity holding data, including the market value investment per country in the equity portfolio. The data provided by Norges Bank is available on a yearly frequency, ranging from 1998 to 2020. Finally, from FTSE Russell, we obtained the list of countries segmented by Developed Markets, Emerging Markets, and Frontier Markets. For the FTSE country breakdown, refer to Table 25.

6 Empirical analysis

This chapter presents the findings of our two-dimensional research. The first stage of our analysis, which comprises The Fund's asset allocation changes, is segmented in three different sections: Tail, Currency, and Terminal Value Analyses. The second stage evaluates market allocation changes for the portfolios' equity share; this only considers tail analysis since we draw similar conclusions for the Currency analysis as the previous stage. We omitted to assess terminal value in this stage. We believe this is only comprehensive and provides us with accurate information from a sustainability perspective when considering The Fund's entire portfolio (Eq-

uity, Fixed Income, and Real Estate). A quantile analysis focusing on the left side tails (5th and 10th quantiles) is applied for this study. The central aspect under review is the downside risk. To avoid confusion, we suggest readers keep in mind Tables 1 and 2, which present previous and current GPF-G's asset and market allocations. References to past asset and market allocations might be confusing. However, these are required to conduct our analysis as the projections into the future used to construct portfolios rely on past allocation weights. All simulations and inferences are based on future estimates over the next 25 years.

6.1 Asset Allocation

6.1.1 Tail Analysis

We start our analysis by running 10,000 iterations and simulating future returns for each asset class over the next 25 years (2021-2046) via bootstrapping with replacement. Subsequently, we build portfolios using the weights displayed in table 1 from Chapter 4 Methodology—Performing Evaluation. The Central Limit Theorem (CLT) theory helps us understand that, in bootstrapping, the samples of returns will have a similar distribution as that of the original returns. However, what will have a normal distribution are the measures of the characteristics of the distribution, i.e., the "set" of standard deviations of the different samples will approximate a normal distribution. This is one of the underlying reasons why we look at the tails. Furthermore, to bring simplicity and order to the beginning of our analysis, we report our findings in the same currency as The Fund reports its figures: the basket currency.

For the tail evaluation, we look at the tail distribution of the following variables: 1) Nominal returns; 2) Standard Deviation; 3) Sharpe Ratio; 4) Drawdown %; 5) Drawdown Time; 6) Semivariance; 7) Excess Kurtosis, 8) Skewness; and 9) Z-scores. All values are reported annually, except for Drawdown % and Time, reported using monthly observations.

Nominal Returns

From analyzing the summary statistics of the yearly Nominal Returns, we find that, for each portfolio, the mean increases for most portfolio allocations, from 5.68% (1998-2007) to 6.60% (2020-2021). The quantile analysis shows interesting results for which negative returns are expected to double, on average, from the original allocation to the current one during the following 25 years (2021-2046). This is somewhat expected given the increased weight of Equities in recent asset allocations. For more statistics, refer to Table 8 in the Appendix.

Standard Deviation

From analyzing the summary statistics of the standard deviations, we find that, for each portfolio, the mean increases for most portfolio allocations, from 6.18% (1998-2007) to 10.28% (2020-2021). The quantile analysis shows interesting results on the right side (90th and 95th quantiles). The expected standard deviation increases around 50% for more recent allocations, which is somewhat expected given the increased exposure into equities and real estate from the original allocation (1998-2007) to the current one (2020-2021). Furthermore, volatility measured in USD is around 10% to 20% greater than when measured in basket and NOK—which is one of the most important currencies for investments. For more

statistics, refer to Table 9 in the Appendix. Standard Deviation itself is not sufficient to draw economic inferences. The following paragraph will look into the Sharpe Ratio scores to discuss the risk/reward profile.

Sharpe Ratio

From analyzing the summary statistics of the Sharpe ratio (SR) distribution, we find that, for each portfolio, the mean decreases in an almost monotonic fashion, from 0.978 (1998-2007) down to 0.554 (2020-2021). The simulations suggest that the minimum (Min) values are expected to become progressively more negative at every asset allocation change. For more statistics, refer to Table 10. Given the SR values, we do not expect the future trade-off between risk and reward to be compensated appropriately. However, this might be the case of a common misinterpretation of a high SR ratio, i.e., a portfolio with low returns and very low volatility will have a higher Sharpe ratio than another portfolio with higher expected returns and acceptable volatility. As per Table 10, we firmly believe that this is the case for the extreme difference in the allocations moving from 1998-2007 (heavy weights in risk-free assets) to 2020-2021 (heavy weights in risky investments).

Drawdown %

From analyzing the summary statistics of the Drawdown % distribution, we find that, for each portfolio, the mean negatively increases, from -12% (1998-2007) up to -25% (2020-2021)—recall that values are reported monthly. For more statistics, refer to Table 11 in the Appendix. Allocations closer to 2020-2021's have a more significant expected Drawdown % with lower minimums lower expected drawdown % in the tails measured as quantiles (5th and 10th quantiles). From this,

we can infer that the downside is expected to increase.

Drawdown Time

From analyzing the summary statistics of the Drawdown Time distribution, we find that, for each portfolio, the mean increases, from 39.34 months for the 1998-2007 allocation up to 63.34 months for the 2020-2021 allocation. In this specific case, since it is impossible to have a negative drawdown time, we do not look at the left side of the distribution but to the right side, as we are interested in prolonged draw-downs. For more statistics, refer to Table 12 in the appendix. Allocations closer to 2020-2021's have a more extensive expected mean drawdown time; this includes the tails measured at the quantiles (90th and 95th quantiles). From this, we can infer that the downside is expected to increase as the fund would take longer, on average, to recover from its previous peak value.

Semivariance

From analyzing the summary statistics of the semivariance distribution, we find that, for each portfolio, the mean increases for the first and last asset allocation changes, from 4.30% (1998-2007) up to 7.17% (2020-2021), and is constant for the remaining changes. For more statistics, refer to Table 13 in the appendix. We report the semivariance results as the squared semi variance better compares the results with standard deviation. We can see across all simulations that squared semivariance is lower than standard deviation, meaning that the volatility of returns below the mean return is lower. However, we can still observe the squared semivariance increasing for more recent allocations and the spread between standard deviation and squared semivariance becoming greater. Hence, we can infer

that there is an increased in expected downside risk.

Excess Kurtosis

From analyzing the summary statistics of the excess kurtosis distribution, we find that, for each portfolio, the mean fluctuates in between the range of -0.21 (1998-2007) and -0.15 (2020-2021). There is no clear pattern that indicates added risk when we utilize kurtosis as a form of measurement. Also, we might expect that increasing the number of iterations will further decrease excess skewness (relatively to the CLT). However, this is computationally expensive and will not be further explored in this paper. For more statistics, refer to Table 14 in the Appendix.

Skewness

From analyzing the summary statistics of the skewness distribution, we find that, for each portfolio, the mean fluctuates in between the range of -0.08 and -0.11 from 1998-2007 to 2020-2021. The asset allocation revision that happened in 2007 substantially increased the weight of equity while lowering that of fixed income. This fundamentally changed the skewness of portfolio returns; the simulation statistics indicate that more recent asset allocations would yield more negative expected skewness. We know that negative skewness means that downside returns tend to be larger than upside returns from the literature review. For more statistics, refer to Table 15 in the appendix.

Z-Score analysis

We look at the Z-scores of the quantiles and compare them with what would be expected from a normal distribution (refer to Tables 26 and 27). In most cases, we

look at the Z-Score of the 5th and 10th quantiles. There are cases, i.e., semivariance, where the metrics cannot be mathematically negative. In such cases, we look for the opposite quantiles, 90th, and 95th quantiles. We find that the Z-Scores have the same interpretation regardless of the currency; thus, only Z-Scores for basket returns are reported and discussed.

For the left tail, we find that, for the 5th and 10th quantiles across all asset allocations and currencies, the expected Z-score tends to be located further to the left than the expected Z-Score (Normal Distribution). We find the only exception to be Excess Kurtosis, which is closer to the mean than expected. We gain insight from measuring the dispersion from the mean and observe that quantiles' average scores are more negative than expected. We infer an increased downside risk across the board. However, we cannot further quantify it as most Z-Scores across all metrics have a similar value—falling within the same interval for most metrics.

For the right tail, we find that, for the 90th and 95th quantiles across all asset allocations and currencies, the simulation's Z-score tends to be below the expected Z-Score (Normal Distribution). The interpretation is unique to each metric, as some metrics indicate a better portfolio's performance if the score is lower despite not taking negative values. Thus, we group them when performing our analyses. For Sharpe Ratio, the higher the Sharpe Ratio, the better. We can observe a lower expected quantile Sharpe Ratio across all simulations and infer from this a lower risk/reward trade-off. On the other hand, according to mathematical and financial theory, metrics such as drawdown time, standard deviation, and semivariance are not expected to be negative. Hence, a lower expected value is better from a risk

point of view. Overall, the results infer that dispersion from the mean is lower than expected. While this might be considered lower expected risk, the results from the Sharpe Ratio Z-Scores suggest that the lower risk does not come with the expected return payoff.

6.1.2 Currency Analysis

One of The Fund's primary mandates is to invest outside of Norway; hence, currency exposure affects the returns. Our analysis includes returns simulated in the same fashion that The Fund reports its portfolio returns: USD, NOK, and basket. Results show that, across all metrics, a portfolio measured in NOK is expected to have smoother returns compared to those of USD and basket. This effect is better observed in the following table, which shows the simulated yearly nominal returns for all asset allocations carried out by The Fund.

In our view, given that the cumulative returns in NOK are more significant than the cumulative returns in basket or USD, there is empirical evidence suggesting that the NOK has, over the sample period, continuously depreciated (cumulatively), reducing the perceived downside risk when measured in NOK. For instance, the current allocation (2020-2021) has an expected nominal yearly return of 6.60% if measured in basket versus 7.63% when measured in NOK —the same effect can be seen in riskiness utilizing standard deviation. In other words, if returns are measured in NOK, the purchase value of The Fund is expected to exhibit lower downside risk and enjoy a greater expected return with lower volatility. Thus, NOK-nominal withdrawals used for budgetary purposes would constitute a smaller fraction of The Fund's value during periods of drawdowns as fewer assets invested in for-

Table 3: Expected Nominal Returns summary statistics
Frequency of returns: yearly

Allocation	Curr	Mean	Std
1998-2007	NOK	6.66%	7.46%
	Basket	5.68%	6.21%
2007-2017	NOK	7.33%	8.85%
	Basket	6.30%	8.89%
2017-2020	NOK	7.39%	8.81%
	Basket	6.26%	8.90%
2020-2021	NOK	7.63%	9.94%
	Basket	6.60%	10.32%

Note: for simplicity purposes, we compiled the asset allocations for 2007-2008, 2008-2010, and 2010-2017 as they exhibit very similar results. Moreover, also for simplicity, we present the results in only two currencies: NOK and Basket.

From the table above, we see that, on average, NOK-denominated returns exhibit higher spreads than the respective returns in USD and Basket currencies of around 0.5%-1.0%. Moreover, we can also expect that volatility (std) is slightly lower in NOK-denominated portfolios.

eign currencies would have to be liquidated to get the exact value in NOK-nominal withdrawals. Suppose the hedge effect holds, according to the simulations. In that case, we could expect that, in the future, the fund would need to liquidate less of the 'investable' currencies to satisfy the spending in NOK. If this relationship does not hold, The Fund will have to liquidate even more assets to compensate for a downside of The Fund's value and the appreciation of the Norwegian krone.

In the following table, we can better observe the currency effect by looking at the Mean Maximum Drawdown % (MMD%). This effect is present in all the forecast asset allocation and portfolio scenarios. Moreover, we can observe that the portfolio in NOK has both a greater expected return and lower volatility than

when compared to the same portfolio measured in USD and a basket of currencies.

Refer to Table 11 in the appendix for complete statistics.

Table 4: Drawdown % summary statistics

Frequency of returns: monthly

Allocation	Curr	Mean	Std
1998-2007	NOK	-14.72%	4.37%
	Basket	-12.95%	3.90%
2007-2017	NOK	-18.86%	5.46%
	Basket	-21.22%	6.42%
2017-2020	NOK	-18.92%	5.46%
	Basket	-21.20%	6.36%
2020-2021	NOK	-22.05%	6.52%
	Basket	-25.49%	7.66%

Note: for simplicity purposes, we compiled the asset allocations for 2007-2008, 2008-2010, and 2010-2017 as they exhibit very similar results. Moreover, also for simplicity, we present the results in only two currencies: NOK and Basket.

From the table above, we see that, on average, NOK-denominated drawdowns exhibit lower spreads than the respective drawdowns in USD and Basket currencies of around 2.0%-3.0%. Moreover, we can also expect that volatility (std) is slightly lower in NOK-denominated portfolios.

All other measures discussed throughout this research paper are also affected by this currency effect. However, they will not be addressed as they have similar interpretations derived from changes in expected returns and riskiness.

6.1.3 Fund Sustainability Analysis

The last part of our analysis comprises measuring the sustainability of The Fund over the long run. For this thesis, we perform different fund allocations for our 25-year investment horizon. As indicated in the Methodology section of this study

(refer to pp. 15 and 16), The Fund's sustainability is measured by conducting a terminal value analysis and assessing the results.

Table 5: Terminal Value (TV) Distribution

Allocation	Currency	TV	ECDF (0)	ECDF (-50%)	ECDF (-80%)
1998-2007	NOK	11.93%	43.77%	2.08%	0.00%
	USD	13.98%	55.69%	5.04%	0.00%
	Basket	-11.49%	71.18%	4.49%	0.00%
2007-2017	NOK	23.04%	38.55%	3.26%	0.00%
	USD	12.78%	49.50%	9.43%	0.00%
	Basket	-1.72%	59.39%	9.67%	0.00%
2017-2020	NOK	21.12%	39.43%	3.34%	0.00%
	USD	11.40%	51.34%	9.08%	0.00%
	Basket	-2.73%	60.42%	9.41%	0.00%
2020-2021	NOK	28.61%	38.05%	4.67%	0.00%
	USD	18.93%	49.19%	11.56%	0.00%
	Basket	4.83%	56.21%	12.04%	0.00%

Note: for simplicity purposes, we compiled the asset allocations for 2007-2008, 2008-2010, and 2010-2017 as they exhibit very similar results.

From the table above, we see that NOK-denominated portfolios exhibit a higher Terminal Value factor. This is in line with a lower probability of The Fund shrinking value in real terms from its 2020 value. USD and Basket currencies exhibit a higher propensity of The Fund reducing in real value in the three scenarios covered by the EDCF. For instance, an ECDF of -50% shows the probability that The Fund's real value will shrink by 50% in 25 years.

The results from table 16 indicate that the average Terminal Value is expected to increase from a highly negative value at -17.68% (1998-2007) to 4.53% in recent years (2020-2021)- results measured in basket currency. It is noteworthy that, as discussed before, one of the most notorious effects comes from the portfolios measured in NOK. This reiterates our inference that the Norwegian Krone has a hedging effect given its cumulative depreciation over the years; thus, leaving a

greater positive terminal value after accounting for inflation and withdrawals.

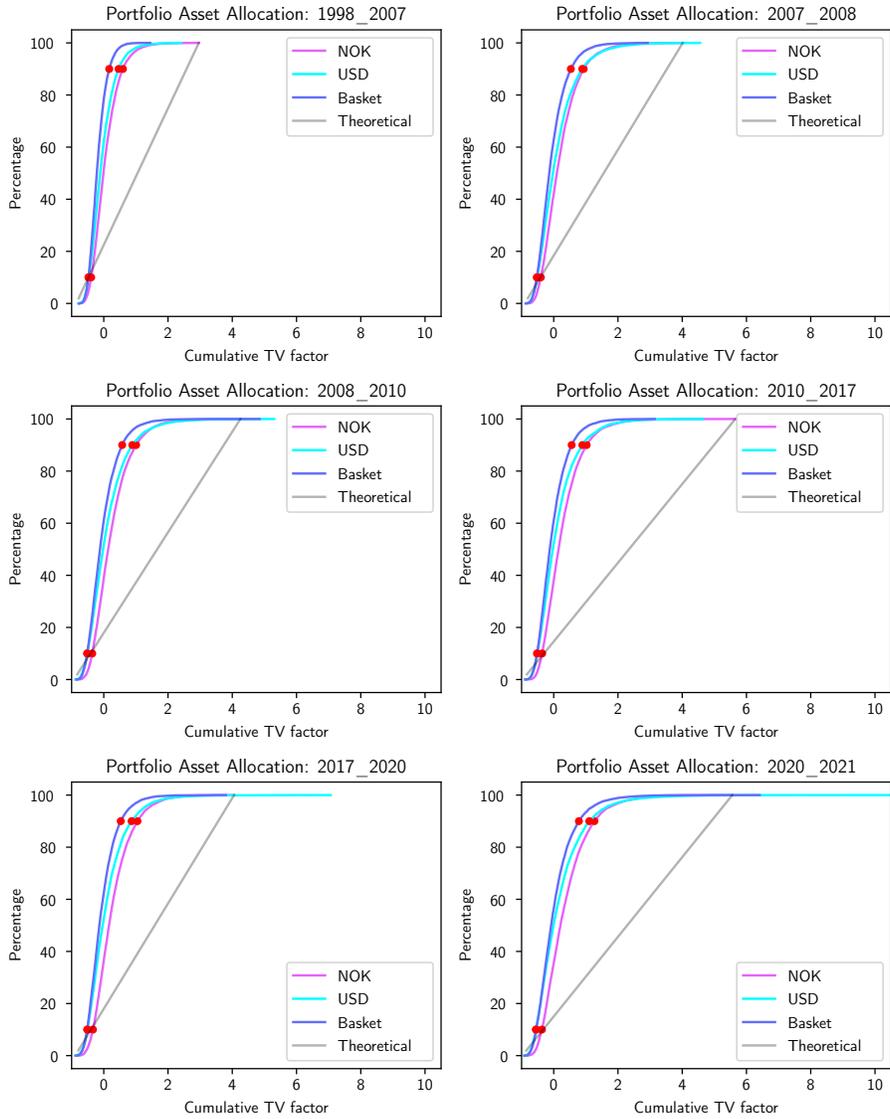
As demonstrated in Figure 1 and Table 5, the empirical cumulative distribution function (ECDF) indicates that the expected probability of a negative terminal value decreases progressively for each asset allocation (basket currency). From this, we can expect that, in the future, the current strategy carried out by The Fund will have an expected lower probability of entering the region where the real value of the fund will shrink after accounting for inflation and withdrawals. There is a lower probability ($P(x < 0)$) of The Fund shrinking in real terminal value in any way in 2046 compared to 2021's value. Nonetheless, we can observe that there is a substantial increase in the probability ($P(x < -0.50)$) of The Fund losing over 50% of its real value- from 4.49% (1998-2007) to 12.04% (2020-2021). In the following plot, we can see that the NOK portfolio tends to be located slightly towards the right side for the six asset allocations forecast, facing the 'theoretical' line of a Normal Distribution.

The red dots in figure A above indicate the 10th and 90th percentiles, and the grey line indicates the theoretical ECDF from a normal distribution. The NOK EDCF plot tends to be below the other two currencies (USD, Basket) for most asset allocations. In other words, it is slightly closer to the normal distribution line compared to the other currencies.

6.2 Equity Share

As mentioned in chapter 4.3 Performing Evaluation, the following analysis was conducted using proxy returns as input to simulate future states of The Fund's

Figure 1: Empirical Cumulative Density Function (ECDF)



equity share. These scenarios might be different if GPF-G's actual returns are used as input for each market allocation.

6.2.1 Tail Analysis

Nominal Returns

From analyzing the summary statistics of the yearly Nominal Returns, we find that, for each portfolio, the mean remains almost unchanged for most portfolio allocations, from 4.75% (1998-2007) to 4.83% (2020-2021). The quantile analysis shows interesting results for which negative returns slightly improve, on average, from the original allocation (1998-2007) to the current one (2020-2021) during the following 25 years (2021-2046). We find it interesting that the changes in market allocations do not seem to come at the expense of future returns. Also, we observe that negative returns when looking at the tails (5th and 10th quantiles) are expected to be progressively lower. For more statistics, refer to Table 17 in the Appendix.

Standard Deviation

From analyzing the summary statistics of the Standard Deviation, we find that, for each portfolio, the mean slightly decreases for most portfolio allocations, from 13.62% (1998-2007) to 12.16% (2020-2021). The quantile analysis (90th and 95th quantiles) shows interesting results for which extreme volatility slightly improves, on average, from the original allocation (1998-2007) to the current one (2020-2021) during the following 25 years (2021-2046). We can also see that the maximums are lower than the initial allocation for most allocations. We find these results striking as the expected returns are increasing while volatility is decreasing, meaning that changes in market allocations do not seem to come at the expense of

future volatility. Standard Deviation itself is not sufficient to draw economic inferences. The following paragraph will look into the Sharpe Ratio scores to discuss the risk/reward profile. For more statistics, refer to Table 18 in the appendix.

Sharpe Ratio

From the discussion of Yearly Nominal Returns and Standard Deviation, we infer that Sharpe Ratios (SR) are expected to improve, supported by the simulation's data. From analyzing the summary statistics of the SR distribution, we find that, for each portfolio, the mean increases in an almost monotonic fashion, from 0.361 (1998-2007) down to 0.410 (2020-2021). The simulations suggest the minimum values are expected to become more negatively extreme at every market allocation change, while the maximums become greater for most cases. For more statistics, refer to Table 19. Given the SR values, we expect the future trade-off between risk/reward to be appropriately compensated for the Equity Share of the portfolio.

Drawdown %

From analyzing the summary statistics of the drawdown % distribution, we find that, for each portfolio, the mean positively increases, from -41.84% (1998-2007) up to -36.53% (2020-2021)— recall that values are reported monthly. For more statistics, refer to Table 20 in the Appendix. From the results, we also learn that diversification into Emerging Markets lowers the riskiness of The Fund when measuring as drawdown %. Allocations closer to 2020-2021's have a lower expected drawdown % with lower negative minimums, while the tails measured as quantiles (5th and 10th quantiles) also experience lower drawdowns. From this, we can infer that the downside is expected to decrease.

Drawdown Time

From analyzing the summary statistics of the drawdown time distribution, we find that, for each portfolio, the mean decreases from 113.57 months (1998-2007) up to 101.71 months (2020-2021). In this specific case, since it is impossible to have negative drawdowns, we do not look at the left side of the distribution but to the right side, as we are interested in prolonged drawdowns. We also learn that diversification into Emerging Markets lowers the mean duration of drawdown as we observe the most significant change in the expected returns from 1998-2007 to 2007-2017. For more statistics, refer to Table 21 in the appendix. Allocations closer to 2020-2021's have a lower expected mean drawdown time; this includes the tails measured at the quantiles (90th and 95th quantiles). We can infer that the downside is likely to decrease as the equity share would take shorter, on average, to recover.

Semivariance

From analyzing the summary statistics of the semivariance distribution, we find that, for each portfolio, the mean decreases from the first to last asset allocation changes, from 9.71% (1998-2007) up to 8.65% (2020-2021), and is constant for the remaining changes. For more statistics, refer to Table 22 in the Appendix. We report the semivariance results as the squared semivariance to better compare these results with standard deviation —refer to Table 18. We can see across all simulations that mean-squared semivariance is lower than mean-standard deviation. Moreover, we observe squared semivariance decreasing for more recent allocations and the spread between standard deviation and squared semivariance remaining sta-

ble across all allocations. Hence, we can infer that there is an expected decrease in downside risk.

Excess Kurtosis

From analyzing the summary statistics of the excess kurtosis distribution, we find that, for each portfolio, the mean fluctuates in between the range of 0.13 (1998-2007) and 0.14 (2020-2021). There is no clear pattern that indicates added risk when we utilize kurtosis as a form of measurement. Also, we might expect that increasing the number of iterations will further decrease excess kurtosis (relatively to the CLT). However, this is computationally expensive and will not be further explored in this paper. For more statistics, refer to Table 23 in the appendix.

Skewness

From analyzing the summary statistics of the skewness distribution, we find that, for each portfolio, the mean fluctuates in between the range of -0.16 (1998-2007) and -0.16 (2020-2021). The inclusion of Emerging Markets in the market allocation revision that happened in 2007 did not change the level of skewness in the equity portion of the portfolio. This is different from the effect that we discussed for the portfolio's asset allocations, where skewness changed due to the increase in weight of the equity share, yielding more negative expected skewness. Moreover, we do not observe any significant changes in both sides of the tail; hence, the insight we gain from the skewness review comes from the discussion in the literature review. We know that negative skewness means that downside returns tend to be larger than upside returns. For more statistics, refer to Table 24 in the appendix.

Z-Score analysis

Similar to what is discussed in Chapter 6.1.2, we find that, for all simulations of market allocations, the Z-Scores for the left and right sides of the distribution tend to be below the expected Z-score values. Therefore, we obtain the same insight of dispersion from the mean in the quantiles as from the previous Z-score analysis under section 6.1 Asset Allocation. Refer to Tables 28 and 29 for more statistics.

7 Conclusion

7.1 Key Findings and Implications

There is empirical evidence to say that the downside risk of the Fund has increased. However, we only find partial evidence indicating that it is excessive. The simulations for the following 25 years show that the more recent asset allocations implemented by The Fund have a progressive lower expected probability of having any negative TV compared to initial allocations. However, we find it concerning that the findings of our analysis suggest that the likelihood of The Fund losing 50% or more of its real value increases from 4.49% to 12.04% if the weights from the current allocation remain the same in the future. From a risk management perspective, we consider this not to be unlikely but a possible occurrence.

The tail analysis performed for the asset allocations (Chapter 6 Empirical Analysis) suggest that the level of riskiness is increasing in the more recent allocations, according to the metrics reported and discussed. We find intriguing the decrease in Sharpe Ratios, which can be interpreted as a poorer trade-off between risk/reward; and the abrupt increase in expected Drawdown % from -12.95% to 25.49% and the

increase in Drawdown Time from 39 to 63 months. These results indicate a substantial increase in downside risk. In addition, the results reported in most of the metrics demonstrate the spread between the mean and median values is marginal. Therefore, we are more confident that the average values are representative of the actual expected values and less prone to be affected by noise during the bootstrapping process (simulations).

Moreover, when considering the equity share of the portfolio, our simulations suggest the addition of equity investments to The Fund's portfolio would increase risk. Also, the inclusion of Emerging and Frontier markets as an extension to a portfolio initially invested in only Developed Markets is expected to reduce future downside risk. Surprisingly, the results indicate a contradiction between our study for the asset and equity allocations, including for the tail analysis. In our view, this might be a consequence of an increase in the covariance between the components in the equity and fixed income shares of the portfolio.

We find that the Fund's current allocation is the only allocation that does not have a negative expected terminal value in the three currencies (NOK, USD, and Basket). However, we also observe an asymmetry effect between positive and negative terminal values as the median exhibits a contradictory view. The only positive terminal value occurs when GPF-G is measured in NOK. Hence, we can say that if The Fund had to withdraw net of its maximum allowance (3% of The Fund's value according to the Budgetary Rule) and global inflation, it would have not, as per our time horizon of 25 years (2021-2046), reached sustainable levels. We acknowledge that the assumption of no inflows and maximum withdrawals does

not represent Norway and The Fund's current and expected economic conditions. However, our goal is to gain insights into all sustainability scenarios. Additionally, The Fund's value cannot be negative. Its returns might be since withdrawals tend to be proportional, and we find them unlikely to reduce GPF-G's value to zero. Also, the conclusion drawn is tied back to our initial motivation: understanding how GPF-G influences the Norwegian economy and assessing its asset allocation changes to make inferences about sustainability over the long term. Lastly, it becomes clear from this study that the added risk is being compensated with higher returns when considering our terminal value analysis. On the other hand, there is a lower probability of The Fund losing any of its value in real terms, the same way that the possibility of extreme losses in the future is increased.

7.2 Limitations and Guidelines for Future Research

The Fund has been the center of academic research for years, given its transparency and social and economic importance. However, researchers have focused mainly on backtesting and past-looking performance. This paper brings insights into a topic that has not yet been as widely explored, and, for this thesis, we consider future states of The Fund given all the past asset and market allocations.

Limitations

There have been some limitations on the data available that have prevented us from conducting a deeper and closer-to-reality analysis. First, we could not find in public databases— i.e., Bloomberg, Refinitiv, or Norges Bank's database and reports—a historical breakdown of monthly returns by markets; hence, we used proxy

indexes from FTSE. This might bias our key findings as the input returns to our models are different from The Fund's realized returns. Second, we were not able to find a test to measure the significance of the tails to evaluate the robustness of the strategies adopted by The Fund.

Future Research

Future research could look at the following points: 1) analysis of the covariance between the Equity and Fixed Income portions of the portfolio. If possible, a deep study into the covariance of market exposure between Equity and Fixed Income. Our conclusion finds significant differences between the expected returns and downside risk when analyzing the equity share and asset allocations. We infer this is related to this topic. 2) analysis of the Fixed Income share of the portfolio, similarly to our study of the equity share; 3) factor analysis within the equity share, where the changes in factor exposure since The Fund's inception are explored; and 4) our research assumes that the maximum withdrawal allowance by the handlingsreglen is executed every year considering that there are no inflows in the following 25 years. It would be interesting to examine the progressive exhaustion of oil reserves and inflows to The Fund and subsequently measure the impact on The Fund's sustainability.

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9 Appendix

Figure 2: Summary of Variables

Statistic	Definition	Formula	Interpretation
Sharpe Ratio	Average return earned in excess of the risk-free rate per unit of volatility or total risk.	$SR = \frac{R_p - R_f}{\rho_p}$	A High Share ratio is preferable (higher return relative to risk)
Drawdown (DD)	Refers to how much an investment is down from the peak before it recovers back to the peak.	$MDD = \frac{High - Low}{High}$	Smaller is preferable (less time to recover)
Semivariance	Dispersion of all observations that fall below the mean or target value of a set of data	$SV = \frac{1}{n} * \sum (\bar{X} - X)^2$	Lower is preferable (less risk in the observed data)
Kurtosis	Measures extreme values in either tail of the distribution.	$Kurtosis = \frac{\mu_4}{\mu_2^2}$	High kurtosis implies occasional extreme returns (either positive or negative).
Skewness	Refers to a distortion or asymmetry that deviates from the symmetrical bell curve.	$Skewness = \frac{\mu_3}{\mu_2^3}$	Extent to which a distribution varies from a normal distribution (skew=0)

Note: The table above contains a summary of the variables mentioned in this thesis.

Figure 3: Backtesting Asset Allocation

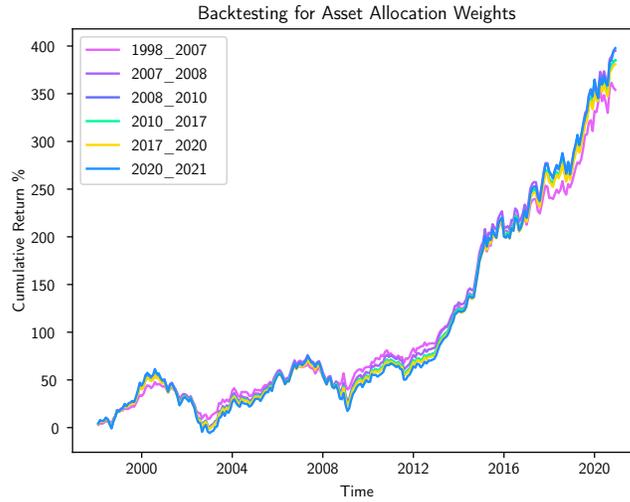
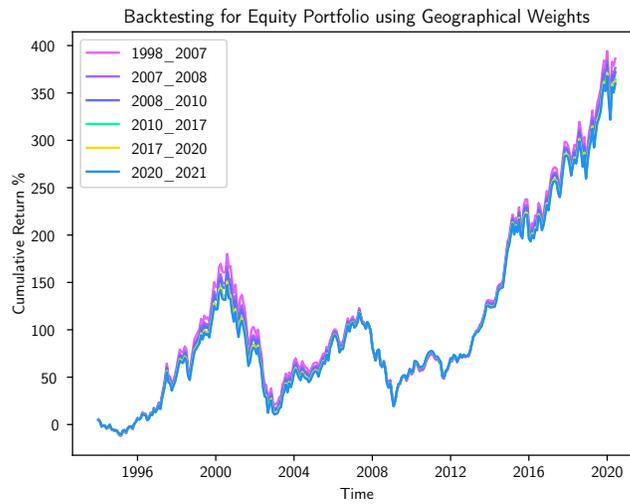


Figure 4: Backtesting Equity Allocation



The exhibits show the backtesting plots for different the strategies in asset allocation and market allocations carried out by The Fund since its inception. The first plot (Figure 3) illustrates the backtesting of the asset allocation changes from 1998 to 2020. The second plot (Figure 4) illustrates the backtesting of the market allocations changes from 1996 to 2020.

Table 6: Basket Returns' Calculation Methodology

Given that returns for the proxy indexes are not available in the same basket of currencies used by NBIM-The Fund, we transform the proxy returns in USD to basket using a depreciation/appreciation factor denoted as E. Since, the returns correspond to the same period and same portfolio, the difference must be due to changes in currencies.

Step 1: Use The Fund's actual returns for USD and Basket. Solve of for E at each point in time.

$$R_{BRt} = \frac{1+R_{URt}}{1+E_t} - 1 \Rightarrow E_t = 1 - \frac{1+R_{BRt}}{1+R_{URt}}$$

Where:

R_{BRt} = Returns Equity Basket Real

R_{URt} = Returns Equity USD Real

E_t = Appreciation/Depreciation Factor

Step 2: Use proxy's return in USD, and plug E for each point in time.

$$R_{PBt} = \frac{1+R_{PUSDt}}{1+E_t} - 1$$

Where:

R_{PBt} = Proxy Returns Basket Equity Market

R_{PUSDt} = Proxy Returns USD Equity Market

Step 3: Remove Norway's proportional contribution to index's returns.

$$R_{PBt}(ExNorway) = R_{PBt} - (W_{NOR} * R_{NORt})$$

Where:

$R_{PBt}(ExNorway)$ = Proxy Returns Basket Equity Market Excluding Norway

W_{NORt} = Weight of Norway in the proxy index

R_{NORt} = Return of Norway's Market

Table 7: Market Size weights' Calculation Methodology

Given that market weights are not provided by NBIM-The Fund, we use the nominal value in USD for each country in order to group by the countries that make up each market classification according to FTSE. (refer to Table 25) We assume that weights in other currencies are equal to the weights in USD.

Step 1: Group by markets using the nominal investment in USD by market, then calculate weights using the formula.

$$\text{Weight}_t = \frac{\text{Market Value USD Market}_t}{\sum_t \text{Market Value USD Market}_t}$$

Table 8: Nominal Returns summary statistics (Asset Allocation)
Frequency of returns: yearly

Allocation	Curr	Mean	Std	Min	5%	10%	50%	90%	95%	max
1998-2007	NOK	6.66%	7.46%	-27.72%	-5.39%	-2.67%	6.59%	16.31%	18.95%	39.62%
<i>40% Equities</i>	USD	6.27%	7.81%	-31.77%	-6.54%	-3.65%	6.27%	16.25%	19.01%	40.27%
<i>& 60% FI</i>	Basket	5.68%	6.21%	-28.60%	-4.60%	-2.13%	5.77%	13.57%	15.66%	32.90%
2007-2017	NOK	7.33%	8.85%	-35.93%	-7.27%	-3.87%	7.36%	18.70%	21.75%	43.41%
<i>60 % Equities</i>	USD	6.83%	10.23%	-50.48%	-10.20%	-6.13%	6.89%	19.80%	23.39%	49.36%
<i>& ~40% FI</i>	Basket	6.30%	8.89%	-41.88%	-8.58%	-5.01%	6.41%	17.58%	20.59%	45.13%
2017-2020	NOK	7.39%	8.81%	-46.49%	-7.10%	-3.74%	7.44%	18.68%	21.70%	44.45%
<i>60 % Equities</i>	USD	6.78%	10.18%	-52.39%	-10.20%	-6.09%	6.86%	19.72%	23.25%	50.20%
<i>& ~40% FI</i>	Basket	6.26%	8.90%	-46.03%	-8.67%	-5.07%	6.37%	17.51%	20.48%	43.31%
2020-2021	NOK	7.63%	9.94%	-40.76%	-8.81%	-4.94%	7.69%	20.37%	23.76%	46.84%
<i>70 % Equities</i>	USD	7.05%	11.71%	-55.06%	-12.61%	-7.80%	7.51%	21.93%	25.93%	59.36%
<i>& ~30% FI</i>	Basket	6.60%	10.32%	-46.16%	-10.71%	-6.53%	6.73%	19.65%	23.10%	51.91%

Note: for simplicity purposes, we compiled the asset allocations for 2007-2008, 2008-2010, and 2010-2017 as they exhibit very similar results.

The results reported in this table are the product of the average of 10,000 simulations across all asset allocations. The simulations forecast the next 25 years from year 2021 to 2046, and are derived from a bootstrap with replacement methodology. From the reported figures, we can observe that expected returns tend to increase in a quasi-monotonic pattern across all asset allocations (1998-2021) and currencies (NOK, USD, and Basket); expected increase in Downside risk. The increase in expected returns, as seen in the table, comes at the expense of higher volatility, measured in standard deviation (Std). Moreover, when considering left tail percentiles, we observe substantial increase in expected downside returns from the first (1998-2007) to the last (2020-2021) asset allocation (Basket currency). For instance, when considering the 5% percentile for the basket portfolio, we observe a decrease in expected return from -4.60% to -10.71%, respectively. The reported Stds are the cross-simulation average of each simulation return. In other words, it is the standard deviation of the mean return.

Table 9: Standard Deviation summary statistics (Asset Allocation)
Frequency of returns: yearly

Allocation	Curr	Mean	Std	Min	5%	10%	50%	90%	95%	max
1998-2007	NOK	7.42%	1.13%	3.49%	5.61%	6.00%	7.39%	8.90%	9.35%	12.37%
<i>40% Equities</i>	USD	7.73%	1.10%	3.77%	5.97%	6.34%	7.69%	9.18%	9.60%	12.71%
<i>& 60% FI</i>	Basket	6.18%	0.95%	3.30%	4.64%	4.97%	6.15%	7.40%	7.78%	10.38%
2007-2017	NOK	8.80%	1.34%	4.20%	6.68%	7.12%	8.76%	10.56%	11.12%	14.01%
<i>60 % Equities</i>	USD	10.13%	1.48%	5.31%	7.79%	8.25%	10.07%	12.07%	12.66%	16.79%
<i>& ~40% FI</i>	Basket	8.86%	1.37%	4.28%	6.66%	7.13%	8.82%	10.63%	11.20%	16.20%
2017-2020	NOK	8.72%	1.34%	3.49%	6.57%	7.03%	8.68%	10.45%	10.99%	13.79%
<i>60 % Equities</i>	USD	10.07%	1.47%	5.16%	7.75%	8.23%	10.03%	12.00%	12.54%	16.64%
<i>& ~40% FI</i>	Basket	8.86%	1.38%	4.34%	6.65%	7.12%	8.80%	10.68%	11.21%	15.47%
2020-2021	NOK	9.88%	1.51%	4.47%	7.46%	7.95%	9.84%	11.85%	12.46%	15.87%
<i>70 % Equities</i>	USD	11.59%	1.70%	5.90%	8.85%	9.44%	11.56%	13.79%	14.47%	18.93%
<i>& ~30% FI</i>	Basket	10.28%	1.60%	4.52%	7.76%	8.27%	10.24%	12.36%	12.99%	16.70%

Note: for simplicity purposes, we compiled the asset allocations for 2007-2008, 2008-2010, and 2010-2017 as they exhibit very similar results.

The results reported in this table are the product of the average of 10,000 simulations across all asset allocations. The simulations forecast the next 25 years from year 2021 to 2046, and are derived from a bootstrap with replacement methodology. From the reported figures, we can observe that mean standard deviations (Std) seem to increase across all asset allocations (1998-2021) and currencies (NOK, USD, and Basket); expected increase in Downside risk. More interestingly, when considering the right tail percentiles- as Stds cannot assume negative values, we observe substantial increase in expected portfolio riskiness from the first (1998-2007) to the last (2020-2021) asset allocation (Basket currency). For instance, when considering the 95% percentile for the basket portfolio, we observe an increase in expected volatility from 7.78% to 12.99%, respectively. The reported standard deviations are the cross-simulation average of each simulation Std.

Table 10: Sharpe Ratio summary statistics (Asset Allocation)
Frequency of returns: yearly

Allocation	Curr	Mean	Std	Min	5%	10%	50%	90%	95%	max
1998-2007	NOK	0.919	0.240	0.132	0.555	0.631	0.901	1.230	1.344	2.172
<i>40% Equities</i>	USD	0.829	0.238	0.110	0.466	0.537	0.813	1.141	1.244	2.080
<i>& 60% FI</i>	Basket	0.945	0.253	0.187	0.561	0.638	0.925	1.281	1.393	2.297
2007-2017	NOK	0.855	0.244	0.039	0.489	0.558	0.838	1.175	1.283	2.009
<i>60 % Equities</i>	USD	0.692	0.236	-0.109	0.339	0.405	0.676	0.999	1.098	1.769
<i>& ~40% FI</i>	Basket	0.734	0.241	-0.060	0.368	0.441	0.717	1.050	1.153	1.911
2017-2020	NOK	0.865	0.241	0.114	0.500	0.572	0.847	1.181	1.282	2.015
<i>60 % Equities</i>	USD	0.690	0.235	-0.122	0.335	0.404	0.676	0.992	1.099	1.922
<i>& ~40% FI</i>	Basket	0.727	0.236	-0.062	0.373	0.443	0.712	1.031	1.136	1.962
2020-2021	NOK	0.793	0.237	0.028	0.429	0.500	0.780	1.009	1.209	1.873
<i>70 % Equities</i>	USD	0.625	0.232	-0.254	0.270	0.341	0.610	0.924	1.022	1.861
<i>& ~30% FI</i>	Basket	0.664	0.237	-0.238	0.303	0.376	0.649	0.969	1.079	2.097

Note: for simplicity purposes, we compiled the asset allocations for 2007-2008, 2008-2010, and 2010-2017 as they exhibit very similar results.

The results reported in this table are the product of the average of 10,000 simulations across all asset allocations. The simulations forecast the next 25 years from year 2021 to 2046, and are derived from a bootstrap with replacement methodology. From the reported figures, we can observe that mean Sharpe ratios (SR) seem to decrease across all asset allocations (1998-2021) and currencies (NOK, USD, and Basket); expected increase in Downside risk. More interestingly, when considering both the left and right tails of the distribution, we can observe that all SRs are decreasing throughout the years (1998-2021). In other words, the worst scenarios are expected to get worse, and the extreme good scenarios are expected to worsen in more recent allocations. Hence, the overall riskiness of the portfolio allocations is increasing when utilizing SRs as measure. For instance, when considering the 5% percentile for the basket portfolio, we observe a decrease in SR from 0.56 to 0.30, respectively (Basket currency). Likewise, when considering the 95% percentile for the basket portfolio, we observe a decrease in SR from 1.39 to 1.07, respectively. The reported SRs are the cross-simulation average of each simulation SR.

Table 11: Drawdown % summary statistics (Asset Allocation)
Frequency of returns: monthly

Allocation	Curr	Mean	Std	Min	5%	10%	50%	90%	95%	max
1998-2007	NOK	-14.72%	4.37%	-45.73%	-22.88%	-20.57%	-13.97%	-9.86%	-9.06%	-5.54%
<i>40% Equities</i>	USD	-16.83%	5.01%	-47.32%	-26.33%	-23.67%	-15.98%	-11.27%	-10.29%	-6.49%
<i>& 60% FI</i>	Basket	-12.95%	3.90%	-36.78%	-20.30%	-18.08%	-12.32%	-8.67%	-7.87%	-4.23%
2007-2017	NOK	-18.86%	5.46%	-52.84%	-29.34%	-26.14%	-17.98%	-12.72%	-11.57%	-7.30%
<i>60 % Equities</i>	USD	-24.42%	7.26%	-62.96%	-38.14%	-34.19%	-23.22%	-16.23%	-14.73%	-7.97%
<i>& ~40% FI</i>	Basket	-21.22%	6.42%	-55.58%	-33.45%	-29.91%	-20.12%	-14.10%	-12.86%	-7.76%
2017-2020	NOK	-18.92%	5.46%	-56.30%	-29.38%	-26.20%	-18.01%	-12.81%	-11.69%	-7.65%
<i>60 % Equities</i>	USD	-24.10%	7.25%	-64.74%	-38.11%	-34.12%	-23.24%	-16.20%	-14.73%	-7.97%
<i>& ~40% FI</i>	Basket	-21.20%	6.36%	-55.82%	-33.07%	-29.83%	-20.12%	-13.99%	-12.86%	-7.48%
2020-2021	NOK	-22.05%	6.52%	-58.72%	-34.58%	-30.97%	-21.06%	-14.87%	-13.58%	-8.86%
<i>70% Equities</i>	USD	-28.96%	8.55%	-77.65%	-45.18%	-40.62%	-27.62%	-19.19%	-17.50%	-10.07%
<i>& ~30% FI</i>	Basket	-25.49%	7.66%	-68.08%	-39.89%	-35.63%	-24.25%	-16.87%	-15.34%	-9.37%

Note: for simplicity purposes, we compiled the asset allocations for 2007-2008, 2008-2010, and 2010-2017 as they exhibit very similar results.

The results reported in this table are the product of the average of 10,000 simulations across all asset allocations. The simulations forecast the next 25 years from year 2021 to 2046, and are derived from a bootstrap with replacement methodology. From the reported figures, we can observe that mean Drawdown % (DD%) is substantially decreasing across all asset allocations (1998-2021) and currencies (NOK, USD, and Basket); expected increase in Downside risk. More interestingly, we can better see the effect that currencies have on the portfolio, especially the NOK-denominated portfolio. When considering the left tail of the distribution, we can observe that the DD%*s* are decreasing throughout the years (1998-2021). For instance, when considering the 5% percentile for the basket portfolio, we observe a decrease in SR from -20.30% to -39.89%, respectively (Basket currency). The reported DD%*s* are the cross-simulation average of each simulation DD%.

Table 12: Drawdown time summary statistics (Asset Allocation)
Frequency of returns: monthly

Allocation	Curr	Mean	Std	Min	5%	10%	50%	90%	95%	max
1998-2007	NOK	40.32	20.21	8.00	18.00	20.00	35.00	66.00	79.00	208.00
<i>40% Equities</i>	USD	46.53	24.24	9.00	20.00	23.00	40.00	78.00	93.00	245.00
<i>& 60% FI</i>	Basket	39.34	20.17	9.00	17.00	20.00	34.00	65.00	79.00	222.00
2007-2017	NOK	45.64	23.73	9.00	19.00	23.00	40.00	76.00	92.00	231.00
<i>60 % Equities</i>	USD	59.65	33.43	10.00	24.00	28.00	51.00	102.00	127.00	299.00
<i>& ~40% FI</i>	Basket	55.10	30.48	11.00	22.00	26.00	48.00	94.00	114.00	296.00
2017-2020	NOK	44.46	22.86	9.00	19.00	22.00	39.00	73.00	90.00	226.00
<i>60 % Equities</i>	USD	59.53	33.16	11.00	24.00	28.00	51.00	102.00	123.00	299.00
<i>& ~40% FI</i>	Basket	55.27	29.98	10.00	23.00	26.00	48.00	94.10	115.00	299.00
2020-2021	NOK	50.28	26.45	10.00	21.00	25.00	44.00	84.00	102.00	257.00
<i>70 % Equities</i>	USD	67.73	38.23	11.00	26.00	31.00	58.00	117.10	143.00	298.00
<i>& ~30% FI</i>	Basket	63.34	36.15	10.00	25.00	29.00	54.00	109.00	136.00	297.00

Note: for simplicity purposes, we compiled the asset allocations for 2007-2008, 2008-2010, and 2010-2017 as they exhibit very similar results.

The results reported in this table are the product of the average of 10,000 simulations across all asset allocations. The simulations forecast the next 25 years from year 2021 to 2046, and are derived from a bootstrap with replacement methodology. From the reported figures, we can observe that mean Drawdown Time (DDT) is increasing across all asset allocations (1998-2021) and currencies (NOK, USD, and Basket); expected increase in Downside risk. More interestingly, we can observe the buffer effect of the NOK (spending currency) as in the most recent allocations there is a reduction in DDT of approximately 10 months. When considering the left tail of the distribution, we can observe that the DDTs are increasing throughout the years (1998-2021). For instance, when considering the 5% percentile for the basket portfolio, we observe an increase in DDT from 17.00 to 25.00 months, respectively (Basket currency). The reported DDTs are the cross-simulation average of each simulation DDT.

Table 13: Semivariance summary statistics (Asset Allocation)
 Frequency of returns: yearly

Statistic	Curr	Mean	Std	Min	5%	10%	50%	90%	95%	max
1998-2007	NOK	5.08%	0.83%	2.48%	3.79%	4.04%	5.06%	6.16%	6.49%	8.65%
<i>40% Equities</i>	USD	5.37%	0.90%	2.58%	3.98%	4.23%	5.33%	6.55%	6.96%	9.92%
<i>& 60% FI</i>	Basket	4.30%	0.73%	2.12%	3.16%	3.39%	4.26%	5.27%	5.57%	7.93%
2007-2017	NOK	6.09%	1.02%	3.07%	4.47%	4.79%	6.05%	7.42%	7.83%	10.38%
<i>60 % Equities</i>	USD	7.08%	1.23%	3.45%	5.16%	5.53%	6.99%	8.70%	9.23%	12.52%
<i>& ~40% FI</i>	Basket	6.18%	1.08%	2.98%	4.49%	4.81%	6.12%	7.61%	8.07%	10.89%
2017-2020	NOK	6.07%	1.01%	2.60%	4.49%	4.79%	6.03%	7.37%	7.82%	11.39%
<i>60 % Equities</i>	USD	7.04%	1.22%	3.20%	5.14%	5.53%	6.97%	8.66%	9.17%	13.72%
<i>& ~40% FI</i>	Basket	6.19%	1.07%	3.00%	4.53%	4.87%	6.13%	7.61%	8.05%	11.21%
2020-2021	NOK	6.87%	1.15%	3.59%	5.05%	5.42%	6.83%	8.36%	8.83%	11.56%
<i>70 % Equities</i>	USD	8.12%	1.41%	3.84%	5.91%	6.34%	8.06%	9.99%	10.54%	14.35%
<i>& ~30% FI</i>	Basket	7.17%	1.25%	3.44%	5.23%	5.60%	7.10%	8.82%	9.31%	14.03%

Note 1: for standardization of results, the values reported are the square root of the semivariance statistic.

Note 2: for simplicity purposes, we compiled the asset allocations for 2007-2008, 2008-2010, and 2010-2017 as they exhibit very similar results.

The results reported in this table are the product of the average of 10,000 simulations across all asset allocations. The simulations forecast the next 25 years from year 2021 to 2046, and are derived from a bootstrap with replacement methodology. From the reported figures, we can observe that mean Semivariance is increasing across all asset allocations (1998-2021) and currencies (NOK, USD, and Basket); expected increase in Downside risk. More interestingly, when considering the right tail percentiles- as Semivariance cannot assume negative values, we observe substantial increase in expected portfolio riskiness from the first (1998-2007) to the last (2020-2021) asset allocation (Basket currency). For instance, when considering the 95% percentile for the basket portfolio, we observe an increase in expected volatility from 5.57% to 9.31%, respectively. The reported semivariances are the cross-simulation average of each simulation semivariance.

Table 14: Excess Kurtosis summary statistics (Asset Allocation)
Frequency of returns: yearly

Allocation	Curr	Mean	Std	Min	5%	10%	50%	90%	95%	max
1998-2007	NOK	-0.26	0.70	-1.58	-1.10	-0.97	-0.40	0.62	1.07	5.92
<i>40% Equities</i>	USD	-0.20	0.75	-1.67	-1.07	-0.95	-0.37	0.73	1.23	6.19
<i>& 60% FI</i>	Basket	-0.21	0.78	-1.61	-1.09	-0.97	-0.38	0.73	1.21	8.53
2007-2017	NOK	-0.26	0.72	-1.51	-1.10	-0.98	-0.41	0.64	1.10	6.09
<i>60 % Equities</i>	USD	-0.14	0.80	-1.52	-1.05	-0.93	-0.32	0.83	1.33	7.51
<i>& ~40% FI</i>	Basket	-0.17	0.78	-1.61	-1.07	-0.94	-0.35	0.79	1.29	6.47
2017-2020	NOK	-0.24	0.73	-1.61	-1.10	-0.98	-0.39	0.67	1.13	8.10
<i>60 % Equities</i>	USD	-0.16	0.80	-1.48	-1.06	-0.94	-0.33	0.80	1.31	8.29
<i>& ~40% FI</i>	Basket	-0.18	0.78	-1.58	-1.07	-0.95	-0.35	0.77	1.28	8.65
2020-2021	NOK	-0.23	0.73	-1.52	-1.08	-0.96	-0.38	0.66	1.12	5.94
<i>70 % Equities</i>	USD	-0.13	0.82	-1.54	-1.05	-0.92	-0.32	0.86	1.41	7.68
<i>& ~30% FI</i>	Basket	-0.15	0.80	-1.48	-1.06	-0.93	-0.33	0.81	1.35	9.00

Note: for simplicity purposes, we compiled the asset allocations for 2007-2008, 2008-2010, and 2010-2017 as they exhibit very similar results.

The results reported in this table are the product of the average of 10,000 simulations across all asset allocations. The simulations forecast the next 25 years from year 2021 to 2046, and are derived from a bootstrap with replacement methodology. From the reported figures, we can observe that mean Excess Kurtosis tends to be stable across all asset allocations (1998-2021) and currencies (NOK, USD, and Basket). More interestingly, we can see that the NOK-denominated portfolios have a lighter tail compared to the other currencies (USD, Basket) in all scenarios. We do not seem to obtain any evidence of increased Downside risk from the Excess Kurtosis measure.

Table 15: Skewness summary statistics (Asset Allocation)
Frequency of returns: yearly

Allocation	Curr	Mean	Std	Min	5%	10%	50%	90%	95%	max
1998-2007	NOK	0.02	0.41	-1.85	-0.66	-0.50	0.02	0.53	0.69	1.66
<i>40% Equities</i>	USD	-0.03	0.43	-2.22	-0.77	-0.58	-0.02	0.49	0.66	1.86
<i>& 60% FI</i>	Basket	-0.08	0.43	-2.59	-0.80	-0.62	-0.07	0.45	0.61	2.29
2007-2017	NOK	-0.04	0.41	-2.00	-0.73	-0.56	-0.03	0.47	0.62	1.87
<i>60 % Equities</i>	USD	-0.08	0.44	-2.36	-0.82	-0.64	-0.66	0.46	0.62	2.33
<i>& ~40% FI</i>	Basket	-0.10	0.44	-2.15	-0.84	-0.66	-0.09	0.43	0.59	1.69
2017-2020	NOK	-0.05	0.42	2.26	-0.76	-0.59	-0.04	0.48	0.64	1.86
<i>60 % Equities</i>	USD	-0.08	0.44	-2.32	-0.82	-0.64	-0.07	0.47	0.63	1.87
<i>& ~40% FI</i>	Basket	-0.11	0.44	-2.59	-0.85	-0.66	-0.09	0.43	0.58	2.16
2020-2021	NOK	-0.06	0.42	-2.00	-0.77	-0.59	-0.05	0.46	0.62	1.67
<i>70 % Equities</i>	USD	-0.10	0.45	-2.29	-0.86	-0.66	-0.09	0.45	0.61	1.78
<i>& ~30% FI</i>	Basket	-0.11	0.44	-2.65	-0.87	-0.67	-0.10	0.42	0.58	1.79

Note: for simplicity purposes, we compiled the asset allocations for 2007-2008, 2008-2010, and 2010-2017 as they exhibit very similar results.

The results reported in this table are the product of the average of 10,000 simulations across all asset allocations. The simulations forecast the next 25 years from year 2021 to 2046, and are derived from a bootstrap with replacement methodology. From the reported figures, we can observe that the mean Skewness tends to be negative and to decrease across all asset allocations (1998-2021) and currencies (NOK, USD, and Basket). In other words, on average, the returns are more likely to experience small negative returns and smaller-extreme negative returns.

Table 16: Terminal Value summary statistics (Asset Allocation)
Frequency of returns: yearly

Allocation	Curr	Mean	Std	Min	5%	10%	50%	90%	95%	max
1998-2007	NOK	6.18%	41.37%	-78.12%	-46.89%	-39.18%	-0.91%	59.64%	83.63%	295.84%
<i>40% Equities</i>	USD	-4.18%	39.05%	-79.19%	-54.12%	-46.88%	-11.12%	46.14%	68.37%	241.21%
<i>& 60% FI</i>	Basket	-17.68%	26.17%	-76.36%	-53.65%	-47.74%	-21.61%	16.99%	31.41%	144.60%
2007-2017	NOK	26.27%	59.14%	-83.35%	-45.76%	-35.99%	14.79%	102.52%	136.27%	565.21%
<i>60 % Equities</i>	USD	10.80%	60.85%	-88.85%	-59.66%	-50.73%	-2.55%	89.16%	131.25%	464.71%
<i>& ~40% FI</i>	Basket	-3.30%	45.71%	-88.65%	-59.36%	-52.05%	-12.42%	55.90%	81.81%	314.33%
2017-2020	NOK	27.78%	57.77%	-79.01%	-43.89%	-33.69%	16.23%	104.85%	138.26%	405.77%
<i>60 % Equities</i>	USD	9.64%	60.68%	-89.06%	-59.54%	-50.89%	-3.42%	86.63%	123.59%	706.45%
<i>& ~40% FI</i>	Basket	-4.63%	44.93%	-86.65%	-58.99%	-51.48%	-13.68%	52.81%	80.46%	380.04%
2020-2021	NOK	35.97%	70.48%	-85.21%	-47.65%	-36.80%	21.09%	126.76%	165.91%	555.85%
<i>70 % Equities</i>	USD	17.71%	76.84%	-92.12%	-64.36%	-55.56%	-6.91%	110.80%	158.86%	1049.97%
<i>& ~30% FI</i>	Basket	4.53%	58.72%	-91.00%	-62.67%	-54.65%	-8.31%	78.39%	114.46%	641.00%

Note 1: Terminal Value (TV) is the cumulative return net of withdrawals and average global inflation for the last three years (2018-2020). A TV of 0 would mean that in the next 25 years (2021-2046), the fund is expected to break-even in real terms.

Note 2: for simplicity purposes, we compiled the asset allocations for 2007-2008, 2008-2010, and 2010-2017 as they exhibit very similar results.

The results reported in this table are the product of the average of 10,000 simulations across all asset allocations. The simulations forecast the next 25 years from year 2021 to 2046. From the reported figures, we can observe that the mean TV tends to increase across all asset allocations (1998-2021) and currencies (NOK, USD, and Basket). It is noteworthy to mention that today's current asset allocation is the only to achieve complete sustainability in all three currencies when looking at the mean TV. However, it is also noteworthy to acknowledge that the mean and the median (50th quantile) are different from each other; the latter is less sensitive to outliers in the dataset.

Table 17: Expected Nominal Returns summary statistics (Equity Share)
Frequency of returns: yearly

Allocation	Curr	Mean	Std	Min	5%	10%	50%	90%	95%	max
1998-2007	NOK	6.70%	13.90%	-56.76%	-16.62%	-11.13%	6.92%	24.32%	29.13%	64.13%
<i>100% DM</i>	USD	5.92%	14.60%	-76.94%	-18.87%	-12.89%	6.38%	24.24%	29.20%	65.11%
	Basket	4.75%	13.76%	-65.06%	-18.72%	-13.09%	5.21%	21.96%	26.51%	58.54%
2007-2017	NOK	6.65%	12.55%	-56.78%	-14.32%	-9.45%	6.79%	22-61%	27-04%	58.85%
<i>89.46 % DM</i>	USD	5.90%	13.27%	-65.92%	-16.56%	-11.16%	6.27%	22.53%	27.11%	63.30%
<i>& 10.50% EM</i>	Basket	4.81%	12.47%	-61.97%	-16.39%	-11.30%	5.22%	20.49%	24.63%	53.68%
2017-2020	NOK	6.67%	12.50%	-57.45%	-14.24%	-9.39%	6.81%	22.57%	26.91%	63.30%
<i>88.96% DM</i>	USD	6.00%	13.21%	-65.94%	-16.34%	-11.04%	6.38%	22.57%	27.08%	61.97%
<i>& 10.81% EM</i>	Basket	4.82%	12.39%	-53.26%	-16.27%	-11.22%	5.23%	20.43%	24.48%	54.27%
2020-2021	NOK	6.65%	12.36%	-57.56%	-14.01%	-9.24%	6.83%	22-37%	26.72%	58.95%
<i>87.71% DM</i>	USD	5.94%	13.08%	-64.99%	-16.16%	-10.86%	6.28%	22.36%	26.80%	58.49%
<i>& 12.11% EM</i>	Basket	4.83%	12.29%	-64.54%	-16.10%	-11.08%	5.24%	20.23%	24.27%	54.98%

Note: for simplicity purposes, we compiled the asset allocations for 2007-2008, 2008-2010, and 2010-2017 as they exhibit very similar results.

The results reported in this table are the product of the average of 10,000 simulations across all asset allocations. The simulations forecast the next 25 years from year 2021 to 2046, and are derived from a bootstrap with replacement methodology. From the reported figures, we can observe that expected returns tend to slightly decrease across all market allocations (1998-2021) and currencies (NOK, USD, and Basket), subsequently, we see the same effect when considering volatility (Std). We do not observe significant variation in expected returns across all market allocations and currencies. Moreover, the values from both tails, left and right side, are to be standardized across all market allocations and currencies. We consider the changes in tails to be marginal; thus, no further comments are provided. The reported returns are the cross-simulation average of each simulation returns.

Table 18: Standard Deviation summary statistics (Equity Share)
Frequency of returns: yearly

Allocation	Curr	Mean	Std	Min	5%	10%	50%	90%	95%	max
1998-2007	NOK	13.76%	1.97%	7.31%	10.60%	11.25%	13.73%	16.36%	17.08%	22.90%
<i>100% DM</i>	USD	14.46%	2.11%	7.41%	11.09%	11.74%	14.39%	17.21%	18.08%	23.44%
	Basket	13.62%	1.97%	6.96%	19.50%	11.12%	13.56%	16.20%	16.93%	20.95%
2007-2017	NOK	12.43%	1.76%	6.69%	9.57%	10.18%	12.37%	14.69%	15.38%	19.91%
<i>89.46% DM</i>	USD	13.13%	1.91%	6.76%	10.05%	10.69%	13.08%	15.62%	16.39%	21.57%
<i>& 10.50% EM</i>	Basket	12.34%	1.79%	6.53%	9.49%	10.08%	12.28%	14.67%	15.37%	20.57%
2017-2020	NOK	12.38%	1.76%	6.17%	9.55%	10.14%	12.35%	14.65%	12.34%	19.96%
<i>88.96% DM</i>	USD	13.07%	1.91%	6.37%	9.89%	10.53%	12.89%	15.39%	16.18%	20.22%
<i>& 10.81% EM</i>	Basket	12.26%	1.78%	5.93%	9.44%	10.00%	12.20%	14.60%	15.27%	19.11%
2020-2021	NOK	12.23%	1.77%	6.32%	9.35%	9.96%	12.19%	14.55%	15.25%	19.77%
<i>87.71% DM</i>	USD	12.93%	1.91%	6.37%	9.89%	10.53%	12.89%	15.39%	16.18%	20.22%
<i>& 12.11% EM</i>	Basket	12.16%	1.68%	5.79%	9.35%	9.92%	12.11%	14.48%	15.18%	21.10%

Note: for simplicity purposes, we compiled the asset allocations for 2007-2008, 2008-2010, and 2010-2017 as they exhibit very similar results.

The results reported in this table are the product of the average of 10,000 simulations across all asset allocations. The simulations forecast the next 25 years from year 2021 to 2046, and are derived from a bootstrap with replacement methodology. From the reported figures, we can observe that mean standard deviations (Std) seem to decrease across all market allocations (1998-2021) and currencies (NOK, USD, and Basket). More interestingly, when considering the right tail percentiles— as Stds cannot assume negative values, we do not observe increase in expected portfolio riskiness from the first (1998-2007) to the last (2020-2021) market allocation (Basket currency). For instance, when considering the 95% percentile for the basket portfolio, we observe a decrease in expected volatility from 16.93% to 15.18%, respectively. The reported standard deviations are the cross-simulation average of each simulation Std.

Table 19: Sharpe Ratio summary statistics (Equity Share)
Frequency of returns: yearly

Allocation	Curr	Mean	Std	Min	5%	10%	50%	90%	95%	max
1998-2007	NOK	0.499	0.221	-0.395	0.157	1.228	0.490	0.786	0.871	1.580
<i>100% DM</i>	USD	0.422	0.220	-0.337	0.084	0.154	0.410	0.705	0.798	1.651
	Basket	0.361	0.221	-0.393	0.012	0.087	0.354	0.646	0.740	1.372
2007-2017	NOK	0.548	0.225	-0.189	0.198	0.269	0.539	0.837	0.929	1.487
<i>89.46 % DM</i>	USD	0.463	0.226	-0.231	0.116	0.185	0.451	0.757	0.856	1.696
<i>& 10.50% EM</i>	Basket	0.402	0.219	-0.309	0.062	0.132	0.391	0.686	0.783	1.545
2017-2020	NOK	0.552	0.222	-0.235	0.205	0.279	0.542	0.837	0.935	1.672
<i>88.96% DM</i>	USD	0.473	0.334	-0.323	0.129	0.200	0.460	0.763	0.865	1.574
<i>& 10.81% EM</i>	Basket	0.405	0.218	-0.462	0.064	0.138	0.394	0.688	0.780	1.398
2020-2021	NOK	0.557	0.226	-0.300	0.206	0.282	0.544	0.845	0.952	1.847
<i>87.71% DM</i>	USD	0.473	0.227	-0.303	0.118	0.193	0.463	0.763	0.862	1.513
<i>& 12.11% EM</i>	Basket	0.410	0.222	-0.593	0.063	0.135	0.400	0.696	0.790	1.444

Note: for simplicity purposes, we compiled the asset allocations for 2007-2008, 2008-2010, and 2010-2017 as they exhibit very similar results.

The results reported in this table are the product of the average of 10,000 simulations across all asset allocations. The simulations forecast the next 25 years from year 2021 to 2046, and are derived from a bootstrap with replacement methodology. From the reported figures, we can observe that mean Sharpe ratios (SR) seem to increase in a monotonic pattern across all market allocations (1998-2021) and currencies (NOK, USD, and Basket). More interestingly, when considering both the left and right tails of the distribution, we can observe that all SRs are increasing throughout the years (1998-2021). In other words, the worst and extremely good scenarios are expected to improve towards more recent allocations. Hence, the overall riskiness of the portfolio allocations is decreasing when utilizing SRs as measure. For instance, when considering the 95% percentile for the basket portfolio, we observe an increase in SR from 0.740 to 0.790. The reported SRs are the cross-simulation average of each simulation SR.

Table 20: Drawdown % summary statistics (Equity Share)
Frequency of returns: monthly

Allocation	Curr	Mean	Std	Min	5%	10%	50%	90%	95%	max
1998-2007	NOK	-36.81%	20.32%	-80.03%	-55.67%	-50.70%	-35.37%	-24.79%	-22.67%	-13.75%
<i>100% DM</i>	USD	-41.53%	11.25%	-87.23%	-62.49%	-57.17%	-40.14%	-28.13%	-25.51%	-14.66%
	Basket	-41.84%	11.82%	-84.77%	-64.01%	-58.37%	-40.27%	-27.93%	-25.22%	-14.80%
2007-2017	NOK	-32.55%	9.25%	-77.84%	-50.16%	-45.15%	-31.05%	-22.12%	-20.08%	-12.04%
<i>89.46% DM</i>	USD	-37.22%	10.57%	-81.81%	-57.09%	-51.75%	-35.75%	-25.00%	-22.56%	-14.06%
<i>& 10.50% EM</i>	Basket	-37.03%	10.56%	-82.47%	-56.67%	-51.53%	-35.50%	-24.77%	-22.49%	-12.76%
2017-2020	NOK	-32.32%	9.05%	-75.85%	-49.15%	-44.53%	-30.84%	-22.03%	-20.04%	-13.11
<i>88.96% DM</i>	USD	-36.61%	10.43%	-80.29%	-56.17%	-51.07%	-35.10%	-24.57%	-22.36%	-13.23%
<i>& 10.81% EM</i>	Basket	-36.81%	10.62%	-84.65%	-56.52%	-51.44%	-35.37%	-24.33%	-22.25%	-14.41%
2020-2021	NOK	-31.79%	8.91%	-77.13%	-48.42%	-43.80%	-30.57%	-21.46%	-19.55%	-12.37%
<i>87.71% DM</i>	USD	-36.34%	10.47%	-85.68%	-55.78%	-50.75%	-34.86%	-24.08%	-21.75%	-13.22%
<i>& 12.11% EM</i>	Basket	-36.53%	10.61%	-84.59%	-56.51%	-51.19%	-34.98%	-24.14%	-22.17%	-13.54%

Note: for simplicity purposes, we compiled the asset allocations for 2007-2008, 2008-2010, and 2010-2017 as they exhibit very similar results.

The results reported in this table are the product of the average of 10,000 simulations across all asset allocations. The simulations forecast the next 25 years from year 2021 to 2046, and are derived from a bootstrap with replacement methodology. From the reported figures, we can observe that mean Drawdown % (DD%) is decreasing across all market allocations (1998-2021) and currencies (NOK, USD, and Basket); expected decrease in Downside risk. More interestingly, we can better see the effect that currencies have on the portfolio, especially the NOK-denominated portfolio. When considering the left tail of the distribution, we can observe that the DD%*s* are decreasing throughout the years (1998-2021). For instance, when considering the 5% percentile for the basket portfolio, we observe an increase in SR from -64.01% to -56.51%. The reported DD%*s* are the cross-simulation average of each simulation DD%.

Table 21: Drawdown Time summary statistics (Equity Share)
Frequency of returns: monthly

Allocation	Curr	Mean	Std	Min	5%	10%	50%	90%	95%	max
1998-2007	NOK	86.37	49.17	13.00	32.00	38.00	74.00	154.00	186.00	299.00
<i>100% DM</i>	USD	101.45	57.40	15.00	36.00	43.00	86.00	182.00	223.00	299.00
	Basket	113.57	63.08	16.00	39.00	47.00	98.00	210.00	248.00	299.00
2007-2017	NOK	78.43	45.29	14.00	29.00	35.00	66.00	140.00	172.00	299.00
<i>89.46 % DM</i>	USD	93.52	53.71	11.00	33.00	39.00	80.00	168.00	207.05	299.00
<i>& 10.50% EM</i>	Basket	103.38	57.88	14.00	37.00	44.00	88.00	187.00	224.00	299.00
2017-2020	NOK	77.61	44.69	14.00	30.00	35.00	66.00	137.00	166.00	299.00
<i>88.96% DM</i>	USD	91.17	52.44	14.00	33.00	29.00	77.00	164.00	199.00	299.00
<i>& 10.81% EM</i>	Basket	102.68	57.59	14.00	36.00	43.00	88.00	186.00	223.00	299.00
2020-2021	NOK	76.56	43.81	13.00	29.00	34.00	65.00	134.00	165.00	299.00
<i>87.71% DM</i>	USD	91.51	53.05	13.00	32.00	39.00	78.00	164.00	204.00	299.00
<i>& 12.11% EM</i>	Basket	101.71	57.28	14.00	36.00	43.00	87.00	185.00	224.00	299.00

Note: for simplicity purposes, we compiled the asset allocations for 2007-2008, 2008-2010, and 2010-2017 as they exhibit very similar results.

The results reported in this table are the product of the average of 10,000 simulations across all asset allocations. The simulations forecast the next 25 years from year 2021 to 2046, and are derived from a bootstrap with replacement methodology. From the reported figures, we can observe that mean Drawdown Time (DDT) is decreasing across all market allocations (1998-2021) and currencies (NOK, USD, and Basket). More interestingly, we can observe the buffer effect of the NOK (spending currency) as in the most recent allocations there is a reduction in DDT of approximately 10 months. When considering the right tail of the distribution, we can observe that the DDTs is expected to decrease throughout the allocations (1998-2021). For instance, when considering the 95% percentile for the basket portfolio, we observe a decrease in DDT from 248.00 to 224.00 months. The reported DDTs are the cross-simulation average of each simulation DDT.

Table 22: Semivariance summary statistics (Equity Share)
Frequency of returns: yearly

Allocation	Curr	Mean	Std	Min	5%	10%	50%	90%	95%	max
1998-2007	NOK	9.66%	1.62%	4.72%	7.07%	7.59%	9.62%	11.80%	12.48%	16.40%
<i>100% DM</i>	USD	10.26%	1.78%	3.96%	7.48%	8.03%	10.17%	12.60%	13.39%	17.90%
	Basket	9.71%	1.68%	4.22%	7.06%	7.59%	9.64%	11.93%	12.58%	17.13%
2007-2017	NOK	8.70%	1.45%	4.16%	6.41%	6.86%	8.64%	10.60%	11.15%	15.70%
<i>89.46 % DM</i>	USD	9.30%	1.62%	4.07%	6.77%	7.26%	9.21%	11.41%	12.10%	16.32%
<i>& 10.50% EM</i>	Basket	8.77%	1.51%	4.35%	6.40%	6.89%	8.69%	10.74%	11.41%	17.04%
2017-2020	NOK	8.66%	1.45%	3.95%	6.37%	6.82%	8.61%	10.56%	11.16%	15.36%
<i>88.96% DM</i>	USD	9.26%	1.60%	3.98%	6.81%	7.30%	9.17%	11.36%	12.06%	16.56%
<i>& 10.81% EM</i>	Basket	8.72%	1.51%	4.19%	6.38%	6.84%	8.63%	10.73%	11.34%	15.24%
2020-2021	NOK	8.57%	1.45%	4.05%	6.30%	6.74%	8.48%	10.51%	11.05%	15.34%
<i>70 % Equities</i>	USD	9.15%	1.61%	4.39%	6.61%	7.16%	9.10%	11.22%	11.92%	16.60%
<i>& 12.11% EM</i>	Basket	8.65%	1.51%	4.11%	6.29%	6.79%	8.56%	10.60%	11.27%	16.83%

Note 1: For standardization of results, the values reported are the square root of the semivariance statistic.

Note 2: For simplicity purposes, we compiled the asset allocations for 2007-2008, 2008-2010, and 2010-2017 as they exhibit very similar results.

The results reported in this table are the product of the average of 10,000 simulations across all asset allocations. The simulations forecast the next 25 years from year 2021 to 2046, and are derived from a bootstrap with replacement methodology. From the reported figures, we can observe that mean Semivariance is decreasing across all market allocations (1998-2021) and currencies (NOK, USD, and Basket); expected decrease in Downside risk. More interestingly, when considering the right tail percentiles- as Semivariance cannot assume negative values, we observe a decrease in expected portfolio riskiness from the first (1998-2007) to the last (2020-2021) market allocation (Basket currency). For instance, when considering the 95% percentile for the basket portfolio, we observe an decrease in expected semivariance from 12.58% to 11.27%. The reported semivariances are the cross-simulation average of each simulation semivariance.

Table 23: Excess Kurtosis summary statistics (Equity Share)
Frequency of returns: yearly

Allocation	Curr	Mean	Std	Min	5%	10%	50%	90%	95%	max
1998-2007	NOK	-0.17	0.76	-1.55	-1.06	-0.92	-0.33	0.76	1.21	8.06
<i>100% DM</i>	USD	-0.11	0.81	-1.58	-1.03	-0.91	-0.30	0.86	1.38	8.29
	Basket	-0.13	0.83	-1.52	-1.06	-0.94	-0.31	0.83	1.40	8.73
2007-2017	NOK	-0.17	0.74	-1.46	-1.05	-0.93	-0.33	0.76	1.23	7.80
<i>89.46 % DM</i>	USD	-0.12	0.83	-1.46	-1.05	-0.92	-0.30	0.90	1.45	10.82
<i>& 10.50% EM</i>	Basket	-0.14	0.79	-1.52	-1.05	-0.92	-0.32	0.82	1.32	8.04
2017-2020	NOK	-0.18	0.74	-1.46	-1.05	-0.93	-0.35	0.74	1.21	10.43
<i>88.96% DM</i>	USD	-0.13	0.80	-1.52	-1.05	-0.92	-0.32	0.86	1.42	7.78
<i>& 10.81% EM</i>	Basket	-0.13	0.81	-1.60	-1.05	-0.93	-0.31	0.88	1.36	10.81
2020-2021	NOK	-0.19	0.74	-1.61	-1.05	-0.93	-0.35	0.71	1.20	6.02
<i>87.71% DM</i>	USD	-0.12	0.82	-1.53	-1.04	-0.92	-0.29	0.88	1.39	9.65
<i>& 12.11% EM</i>	Basket	-0.14	0.80	-1.55	-1.06	-0.93	-0.32	0.86	1.37	9.61

Note: for simplicity purposes, we compiled the asset allocations for 2007-2008, 2008-2010, and 2010-2017 as they exhibit very similar results.

The results reported in this table are the product of the average of 10,000 simulations across all asset allocations. The simulations forecast the next 25 years from year 2021 to 2046, and are derived from a bootstrap with replacement methodology. From the reported figures, we can observe that mean Excess Kurtosis tends to be quite stable across all market allocations (1998-2021) and currencies (NOK, USD, and Basket). More interestingly, we can see that the NOK-denominated portfolios have a lighter tail compared to the other currencies (USD, Basket) in all scenarios. In both tails, left and right side, we see quite standardized values regardless the currency or market allocation. Hence, when analyzing extreme values, we do not gain significant insights regarding portfolio's downside risk. The reported Excess Kurtosis are the cross-simulation average of each simulation Excess Kurtosis.

Table 24: Skewness summary statistics (Equity Share)
Frequency of returns: yearly

Allocation	Curr	Mean	Std	Min	5%	10%	50%	90%	95%	max
1998-2007	NOK	-0.08	0.43	-2.47	-0.80	-0.62	-0.07	0.45	0.62	1.94
<i>100% DM</i>	USD	-0.14	0.45	-2.59	-0.90	-0.71	-0.13	0.40	0.57	1.76
	Basket	-0.16	0.45	-2.51	-0.93	-0.73	-0.15	0.37	0.53	1.98
2007-2017	NOK	-0.07	0.43	-2.46	-0.79	-0.61	-0.06	0.47	0.62	1.53
<i>89.46 % DM</i>	USD	-0.14	0.45	-3.00	-0.89	-0.70	-0.12	0.40	0.57	1.59
<i>& 10.50% EM</i>	Basket	-0.14	0.44	-2.10	-0.89	-0.70	-0.13	0.39	0.56	1.50
2017-2020	NOK	-0.07	0.43	-2.93	-0.80	-0.62	-0.06	0.48	0.63	1.73
<i>88.96% DM</i>	USD	-0.13	0.44	-2.48	-0.89	-0.70	-0.12	0.41	0.56	1.72
<i>& 10.81% EM</i>	Basket	-0.15	0.44	-3.00	-0.90	-0.72	-0.14	0.38	0.54	1.64
2020-2021	NOK	-0.06	0.43	-2.06	-0.79	-0.61	-0.06	0.47	0.62	1.65
<i>87.71% DM</i>	USD	-0.13	0.45	-2.83	-0.89	-0.69	-0.12	0.42	0.58	1.53
<i>& 12.11% EM</i>	Basket	-0.16	0.44	-2.91	-0.92	-0.73	-0.15	0.39	0.53	2.02

Note: for simplicity purposes, we compiled the asset allocations for 2007-2008, 2008-2010, and 2010-2017 as they exhibit very similar results.

The results reported in this table are the product of the average of 10,000 simulations across all asset allocations. The simulations forecast the next 25 years from year 2021 to 2046, and are derived from a bootstrap with replacement methodology. From the reported figures, we can observe that the mean Skewness tends to be negative and to be stable across all market allocations (1998-2021) and currencies (NOK, USD, and Basket). In other words, on average, the returns are more likely to experience small negative returns and smaller-extreme negative returns. The reported Excess Kurtosis are the cross-simulation average of each simulation Excess Kurtosis.

Table 25: FTSE Markets Classification

DEVELOPED MARKETS			EMERGING MARKETS		
Americas	EME	Pacific	Americas	EMEA	Asia
Canada	Austria	Australia	Argentina	Czech Republic	China
United States	Belgium	Hong Kong	Brazil	Egypt	India
	Denmark	Japan	Chile	Greece	Indonesia
	Finland	New Zealand	Colombia	Hungary	Korea
	France	Singapore	Mexico	Kuwait	Malaysia
	Germany	Poland	Pakistan	Serbia	
	Ireland		Qatar	Philippines	Slovenia
	Israel		Russia	Taiwan	
	Italy		Saudi Arabia	Thailand	
	Netherlands		South Africa		
	Norway		Turkey		
	Portugal		United Arab		
	Spain		Emirates		
	Sweden		Peru		
	Switzerland				
	United Kingdom				

FRONTIER MARKETS

Europe and CIS	Africa	ME	Asia
Croatia	Kenya	Bahrain	Bangladesh
Estonia	Mauritius	Jordan	Sri Lanka
Iceland	Morocco	Oman	Vietnam
Lithuania	Nigeria		
Kazakhstan	Tunisia		
Romania			
Serbia			
Slovenia			

Table 26: Comparison Z-scores Asset Allocation

Measure		0.05 (-1.645)	0.10 (-1.282)	0.90 (1.282)	0.95 (1.645)
1998-2007	Nominal Returns	-2.097	-1.775		
	Standard Deviation			1.153	1.469
	Sharpe Ratio			1.143	1.509
	Drawdown %	-2.626	-1.575		
	Drawdown Time			0.823	1.335
	Semivariance			1.184	1.574
	Excess Kurtosis	-1.264	-1.155		
	Skewness	-2.211	-1.820		
2007-2017	Nominal Returns	-2.136	-1.804		
	Standard Deviation			1.158	1.479
	Sharpe Ratio			1.159	1.523
	Drawdown %	-2.569	-1.589		
	Drawdown Time			0.822	1.392
	Semivariance			1.164	1.572
	Excess Kurtosis	-1.250	-1.140		
	Skewness	-2.229	-1.831		
2017-2020	Nominal Returns	-2.142	-1.807		
	Standard Deviation			1.179	1.476
	Sharpe Ratio			1.145	1.483
	Drawdown %	-2.581	-1.587		
	Drawdown Time			0.804	1.341
	Semivariance			1.136	1.548
	Excess Kurtosis	-1.244	-1.136		
	Skewness	-2.236	-1.827		

Table 27: Comparison Z-scores Asset Allocation (continued)

Measure		0.05 (-1.645)	0.10 (-1.282)	0.90 (1.282)	0.95 (1.645)
2020-2021	Nominal Returns	-2.146	-1.812		
	Standard Deviation			1.172	1.489
	Sharpe Ratio			1.154	1.491
	Drawdown %	-2.592	-1.623		
	Drawdown Time			0.785	1.312
	Semivariance			1.158	1.562
	Excess Kurtosis	-1.267	-1.157		
	Skewness	-2.196	-1.813		

This table presents the Z-scores of each statistic and draws a comparison to the Z-scores expected from a normal distribution (In parenthesis) at every quantile. It can be seen that the values presented are all to the left of the values expected from a Normal Distribution. All values reported are in basket currency.

Table 28: Comparison Z-scores Equity Share

Measure		0.05 (-1.645)	0.10 (-1.282)	0.90 (1.282)	0.95 (1.645)
1998-2007	Nominal Returns	-2.199	-1.483		
	Standard Deviation			1.171	1.483
	Sharpe Ratio			1.144	1.469
	Drawdown %	-2.372	-1.622		
	Drawdown Time			1.302	1.815
	Semivariance			1.164	1.502
	Excess Kurtosis	-1.225	-1.017		
	Skewness	-2.274	-1.436		
2007-2017	Nominal Returns	-2.201	-1.481		
	Standard Deviation			1.157	1.470
	Sharpe Ratio			1.143	1.478
	Drawdown %	-2.405	-1.620		
	Drawdown Time			1.215	1.766
	Semivariance			1.158	1.484
	Excess Kurtosis	-1.279	-1.051		
	Skewness	-2.233	-1.459		
2017-2020	Nominal Returns	-2.192	-1.480		
	Standard Deviation			1.164	1.466
	Sharpe Ratio			1.137	1.473
	Drawdown %	-2.448	-1.605		
	Drawdown Time			1.245	1.783
	Semivariance			1.164	1.497
	Excess Kurtosis	-1.275	-1.043		
	Skewness	-2.208	-1.437		

Table 29: Comparison Z-scores Equity Share (continued)

	Measure	0.05 (-1.645)	0.10 (-1.282)	0.90 (1.282)	0.95 (1.645)
2020-2021	Nominal Returns	-2.199	-1.483		
	Standard Deviation			1.174	1.492
	Sharpe Ratio			1.150	1.486
	Drawdown %	-2.431	-1.614		
	Drawdown Time			1.227	1.754
	Semivariance			1.186	1.509
	Excess Kurtosis	-1.277	-1.052		
	Skewness	-2.212	-1.462		

This table presents the Z-scores of each statistic and draws a comparison to the Z-scores expected from a normal distribution (In parenthesis) at every quantile. It can be seen that the values presented are all to the left of the values expected from a Normal Distribution. All values reported are in basket currency.