Performance Attribution of Sovereign Wealth Funds: Quantifying the drivers of performance in Turbulent Markets - Evidence from Norway's Government Pension Fund Global

Auteur : Najib, Sami
Promoteur(s) : Hübner, Georges
Faculté : HEC-Ecole de gestion de l'Université de Liège
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Performance Attribution of Sovereign Wealth Funds: Quantifying the drivers of performance in Turbulent Markets – Evidence from Norway's Government Pension Fund Global

Jury:
Supervisor:
Georges HÜBNER
Reader(s):
Patrick SCHWARZ

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Sami NAJIB
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ABSTRACT

Sovereign Wealth Funds (SWFs) are large, state-owned investment funds designed to achieve long-term national benefits. This thesis examines the performance of Norway's Government Pension Fund Global (GPFG), the world's largest SWF, from its launch in 1998 to December 31, 2024, covering periods of market stability as well as major geopolitical crises. The analysis uses the Brinson-Hood-Beebower (BHB) performance attribution model as well as a factor-based approach based on the BHB model as per François and Hübner (2024), mainly breaking down excess returns into allocation, selection, and interaction effects. Return-Based Style Analysis (RBSA) helps identify key drivers of returns, focusing on market risk and investment-grade corporate bonds as significant factors explaining most of the fund’s performance.

The findings show that security selection was the main driver of excess returns through the period, while allocation effects were slightly negative, likely due to the fund's close alignment to its benchmark. During crises, selection effects varied, with strong performance in some years but significant underperformance in others, such as during the 2008 financial crisis. The factor-based model highlights key trends, such as a positive factor selection for the Market return in certain years, offset by a weaker allocation effect, possibly due to losses from sanctions or poor security choices in affected sectors. Interaction effects also helped reduce losses in volatile periods.

This research adds to the SWF literature by combining financial analysis with insights into crisis impacts and offers a clear, robust framework for evaluating SWF performance. It suggests improving security selection, using crisis-responsive benchmarks based on geopolitical risks, and including bond-specific and geopolitical factors in future models. Despite some limitations, such as excluding the real estate and infrastructure compartments due to data issues, this study provides a thorough approach for assessing SWF performance in both stable and turbulent times.

Keywords: Sovereign Wealth Funds, Performance Attribution, Government Pension Fund Global, Brinson-Hood-Beebower Model, Factor-Based Analysis, Geopolitical Risk, Benchmarking

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1. INTRODUCTION

1.1 Background

Sovereign Wealth Funds are government-owned investment vehicles, managing a large amount of public assets, usually derived from revenues of commodity sales, trade surpluses, or other reserves associated with the national fiscal policy of the country. Global SWF assets exceeded $13 trillion in 2025, and they operate today as significant actors in the global financial markets, with the potential to affect multiple sectors of the economy, support it, or be involved in geopolitical issues (Global SWF, 2025). SWFs function differently from pension funds or mutual funds as they have multiple objectives, including preserving wealth for future generations, stabilizing the economy, and promoting certain strategic purposes, thereby complicating their performance assessment (Aizenman & Glick, 2009). Most scholars agree that the first SWF was the Kuwait Investment Authority, established in 1953. Many other SWFs followed in the steps of the Kuwait Investment Authority, established in oil-rich economies with trade surplus like Norway, Saudi Arabia, and Singapore (Rozanov, 2005).

Norway has a dual sovereign wealth fund system made up of the Government Pension Fund Norway (GPFN) and the Government Pension Fund Global. Accordingly, while the GPFN is slightly older, mostly invests in domestic and Scandinavian securities, and is somewhat smaller and with a primarily focus on domestic investments, the GPFG, created in 1990, manages a much larger pool of assets and has a global reach. Furthermore, the GPFN has fewer restrictions when investing domestically, and the GPFG has more international exposure, with public real-time reporting, and stricter transparency requirements, providing far more available data regarding its returns and holdings to specified benchmarks. In this regard, it is more interesting for a detailed performance attribution analysis in this thesis (Norwegian Ministry of Finance, 2024).

Norway's Government Pension Fund Global, managed by Norges Bank Investment Management (NBIM), is the world's largest SWF, with over $1.5 trillion in assets as of 2025. Established in 1990 to manage and invest the nation's vast oil and gas revenues, GPFG invests in over 9,000 companies worldwide and also holds large fixed-income and real estate portfolios (NBIM, 2024). GPFG is unique among SWFs in terms of transparency; since it reports to the Norwegian Ministry of Finance while being guided by the Santiago Principles (IFSWF, 2008), and is extremely committed to transparency, GPFG differs from many other SWFs with less transparency. Because many SWFs lack transparency, the GPFG stands out as an ideal choice for a performance attribution case study. Its mandate focuses on achieving long-term growth while carefully managing risk, requiring well-thought-out plans to adapt to an ever-changing environment.

The performance attribution framework used in this thesis breaks down investment returns into components such as asset allocation (e.g., equities versus bonds) and security selection (within asset classes). The Brinson Hood Beebower (BHB) model measures the contribution of each component to the total excess return and also helps show whether that excess return was driven by strategic or tactical choices (Brinson, Hood, & Beebower, 1986). Factor-based models, such as the Fama-French framework or with the help of Return-Based Style Analysis, can identify key market exposures such as equity, bond, real estate exposures, or investment styles and factors (Fama & French, 1993; Sharpe, 1992). For SWFs, performance attribution is complicated because of the unique nature of their mandates and benchmarking process, which must take into account a shifting strategic mandate. This is even more relevant for the GPFG, which has a self-defined benchmark.

The study period, 1998–2024, includes three significant crises periods: the Global Financial Crisis of 2008, which swiftly wiped out almost a decade of financial returns, led to a global recession, and forced the GPFG to adjust its risk exposures (NBIM, 2009); the COVID-19 pandemic of 2020, which shocked the markets and created a need for strong portfolio rebalancing (NBIM, 2020); and the Ukraine War of 2022, which resulted in material sanctions, energy market shocks, and the GPFG's divestment of Russian assets (NBIM, 2022). These crises highlighted the necessity of studying SWF performance during periods of turbulence.

1.2 Research problem and significance

Evaluating SWF performance is crucial for understanding their economic impact and the effectiveness of their managerial process, yet the current literature often focuses on macroeconomic or governance aspects rather than understanding how their returns are generated. GPFG's performance is particularly relevant due to its size, transparency, and influence on global markets. Its performance is praised by many policymakers, investors, and academics, but attributing these returns to specific decisions (e.g., allocation vs. selection) remains underexplored. This gap is significant because SWFs often operate in volatile markets, where geopolitical and economic shocks, like the 2008, 2020, and 2022 crises, require adaptive strategies.

Measuring how the Government Pension Fund Global earns returns is challenging, specifically in assessing whether its benchmark (equities, fixed income, and real estate and infrastructure, more recently set by the Ministry of Finance) is a suitable representation of its investment strategy over time. The construction of sovereign wealth fund (SWF) benchmarks is a complicated balancing process between a long-term strategy and short-term adaptability. This balancing process is felt the most during periods of financial crisis, when correlations between asset classes can change quickly. This indicates broader challenges faced by sovereign wealth funds attempting to execute investment strategies in global financial markets while aligning with the state's interest with its overall strategic interest, as described by Dixon and Monk (2010) on the relationship between globalization and state sovereignty in the context of SWFs. Understanding how SWFs explain their performance is as important as understanding SWF performance itself, in the light of major market forces and investment mandates. Most of the literature on SWF performance is descriptive, either relative to total returns (aggregate data) or planning relative to governance frameworks such as the Santiago Principles, but lacks the aspect of a deep financial analysis.

This study addresses this gap by applying contemporary performance attribution methods to the GPFG, offering insights into how allocation, selection, interaction, and market factors drive returns. It is significant for:

- SWF Managers: To help them refine investment strategies and benchmark design.
- Policymakers: To assess the GPFG's alignment with national objectives.
- Academics: To advance the literature on SWF financial attribution.

1.3 Research Question and Objectives

This thesis investigates the GPFG's performance attribution from 1998 to 2024, with a strong focus on turbulent markets. It addresses three research questions:

- How do asset allocation, security selection, and interaction effects contribute to GPFG's excess returns?
- Which market factors (e.g., equity, fixed income, or real estate exposures) primarily drive GPFG's performance?
- Does GPFG's benchmark effectively reflect its strategic adjustments during the 2008 Global Financial Crisis, the 2020 COVID-19 pandemic, and the 2022 Ukraine War?

By answering these questions, the main objective is to quantify the contributions of allocation, selection, and interaction using the BHB model, identify the key return drivers through factor-based analysis, and evaluate benchmark flexibility during crises, which will all help provide evidence-based insights for SWFs to enhance their performance measurement.

These questions and objectives aim to fill this specific gap in financial attribution studies, leveraging GPFG's transparency to offer a model for other SWFs.

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1.5 Main findings and contribution

The analysis reveals that the GPFG outperforms its benchmark by 0.79% annually on average, driven primarily by security selection, which contributes 6.36% to excess returns, and equity market exposure, accounting for ~70% of return variation. Allocation effects are positive but smaller, while fixed-income plays a more minor role, reflecting GPFG's current equity-focused portfolio (NBIM, 2024). During the 2008, 2020, and 2022 crises, security selection remained robust, but benchmark rigidity limited outperformance in some crucial periods.

This study contributes to the SWF literature by providing a detailed financial perspective on the performance attribution of a very transparent fund, complementing other macroeconomic and governance-based studies while highlighting the importance of adopting a flexible benchmarks in turbulent markets, with new insights for benchmark design, as well as offering some empirical evidence on the GPFG's active management strategies, which is extremely relevant for SWFs in general and institutional investors.
Thus, the findings suggest that SWFs can enhance their returns through active selection and need benchmarks that adapt to strategic shifts, particularly during crises.

1.6 Thesis Structure

The thesis is structured as follows:

Chapter 1 (Introduction) includes the Background, research questions, findings, and structure. Chapter 2 presents the (Literature Review/Theoretical Framework), including historical research topics on sovereign wealth funds and related topics that are of extreme importance to this study. Chapter 3 (Data and Methodology) describes the data used and introduces the methodology that will be followed in this research, including the BHB model, factor-based analysis, and the multiple data sources. Chapter 4 (Results) presents all the empirical findings on allocation, selection, interaction, and the factor-based model. Chapter 5 (Discussion) includes an Interpretation of the results, implications, and insightful comparisons. Finally, Chapter 6 (Conclusion) draws a summary of all the findings, contributions, and future research.

Additional sections include the Abstract, Executive Summary, Acknowledgements, Table of Contents, List of Abbreviations/Glossary, Appendices, and Bibliography.

1.7 Scope of the Study

1.7.1 Limitations

While this study offers valuable insights into the performance attribution model and factor exposures of the GPFG, several limitations must be acknowledged.

1.7.2 Data constraints:

The analysis relies exclusively on publicly available data from Norges Bank Investment Management (NBIM) reports. Although NBIM is very well known for its high level of transparency, certain details, such as intra-year portfolio adjustments, security-level exposures, or internal risk metrics, are not disclosed in their reports. Similarly, while data related to fixed income and equity investments is relatively detailed, the information provided on unlisted real estate and infrastructure holdings remains limited and lacks the granularity required to be included in this analysis. As a result, these asset classes are excluded from the scope of this study. This limitation may reduce the precision of the factor analysis, particularly during periods of market stress or rebalancing.

1.7.3 Benchmark Specificity:

The GPFG's equity benchmark is customized to reflect the fund's unique investment mandate, including environmental, ethical, and strategic considerations. However, the benchmark is self-reported by NBIM and not publicly verifiable, meaning that the specific composition of the benchmark, such as the exact securities, is not disclosed. This lack of transparency limits the ability to conduct a fully independent analysis or compare the benchmark directly against the fund's actual holdings. Therefore, the findings from this study may not be fully generalizable to other sovereign wealth funds (SWFs), which may operate under different mandates, risk preferences, and asset allocation strategies.

1.7.4 Model Assumptions:

The factor-based attribution model relies on stable, linear relationships between the factors and asset returns; however, during periods of financial crisis, such as the Global Financial Crisis (2008-2009), the COVID-19 pandemic, or the 2022 Ukraine War, the relationship between factors and returns may diverge significantly from that pattern. In these environments, factor sensitivities may significantly shift, which will impact the robustness of the results.

1.7.5 Time-Period Selection

Although the analysis spans over two decades (1998–2024), the segmentation between “calm” and “turbulent” periods is inherently subjective and may not capture all structural breaks or regime changes, especially in financial markets.

1.7.6 Omitted Factors and Simplifications:

While the selected factor models cover a broad range of known drivers of equity returns, they do not account for macroeconomic shocks, geopolitical risks, or policy changes, factors that could materially impact GPFG’s performance over time.

2. LITERATURE REVIEW

2.1 History and Evolution of Sovereign Wealth Funds

2.1.1 Investment Funds

Investment funds are financial instruments that raise capital from investors in order to invest it into a wide portfolio of investments that the individual investor would not normally have access to, as part of the fund's investment mandate (e.g., stocks, bonds, or real estate). The fund's manager then handles the contributions professionally to deliver the highest possible returns relative to the level of risk accepted by the investors. This is different from the investor making his own individual investments, as the fund provides access to diversified portfolios, thereby reducing the risk by diversifying their capital across a limited number of specific securities and asset classes. On the other hand, Sovereign Wealth Funds are investment funds specifically owned and managed by governments to allocate and manage wealth on behalf of an entire country in a manner that is likely to align with long-term goals (for example, saving for the next generation or having funds available to buffer the economy against shocks). As of December 2024, SWF assets exceed $13 trillion, with Norway's Government Pension Fund Global being the largest SWF by asset size, with over $1.5 trillion in assets under management (SWF Institute, 2024).

The main function of investment funds, including SWFs, is to allocate capital strategically to achieve some specific objectives, which can be difficult to define directly, as each type of fund has its own distinct mandate and goals. Funds operate by collecting capital, often from taxes, commodity revenues, or even strategic reserves, and investing it in assets expected to grow over time. Typically, SWFs tend to originate from national budget surpluses accumulated over several years due to favorable fiscal, trade, and macroeconomic positions, alongside long-term budget planning. (Rozanov, 2005).

For SWFs like the GPFG, which was established in 1990 by the Norwegian government, the main invested capital comes from Norway’s large oil and gas revenues, carefully invested globally in over 9,000 companies, bonds, real estate, and infrastructure (NBIM, 2024). Guided by the investment mandate, Managers have to make two key decisions: asset allocation (choosing asset classes, like equities or bonds) and security selection (picking specific investments, like a specific stock). These decisions, essential to the BHB model used in this thesis, determine the excess return and are evaluated against a self-defined benchmark, such as GPFG’s equity and fixed-income index set by the Norwegian Ministry of Finance.

SWFs are different from other investment funds due to their government ownership and diverse goals. Aizenman and Glick (2009) highlight that SWFs pursue objectives beyond pure profit; these goals can include economic stabilization (e.g., offsetting oil price drops) or strategic development (e.g., funding national projects). GPFG’s mandate, for instance, has an emphasis on intergenerational wealth preservation, balancing high returns with low risk, which shapes its shift towards an equity-heavy portfolio (NBIM, 2024). This broad range of objectives makes performance measurement even more interesting, as SWFs must align financial outcomes with national priorities, unlike private funds that focus solely on financial returns. The table below summarizes the various objectives of SWFs, illustrating their unique role compared to other types of investment funds.

Objective	Description	SWF Example
Stabilization	Offset commodity price volatility	Kuwait Investment Authority
Savings	Preserve wealth for future generations	GPFG
Development	Fund national projects or industries	China Investment Corporation

Table 1: SWF Objectives - Adapted from Aizenman and Glick (2009)

2.1.2 History and Evolution of Sovereign Wealth Funds

Sovereign Wealth Funds started as a way for governments to manage large amounts of national wealth, often generated from natural resources like oil. The history of SWFs shows that they began emerging in resource-rich countries to stabilize their economies and save for the future when oil resources started to decline (Aizenman and Glick, 2009), setting the stage for funds like Norway's Government Pension Fund Global, launched by the Norwegian government in 1990 and managed by Norges Bank Investment Management. As of December 2024, SWFs manage over $13 trillion in assets, with the GPFG leading at over $1.5 trillion (SWF Institute, 2024).

The first officially documented SWF, the Kuwait Investment Board, was created in 1953, later becoming the Kuwait Investment Authority (KIA). Bahgat (2010) explains that KIA was set up to invest Kuwait's oil revenues, protecting their economy from oil price swings and building sustainable wealth for future generations after a possible depletion of oil reserves. This model later became a framework for the other oil-rich countries. For example, the United Arab Emirates launched the Abu Dhabi Investment Authority (ADIA) in 1976, and Saudi Arabia established the Public Investment Fund (PIF) in 1971, both funded by massive oil wealth. These early SWFs focused on long-term investments, often in global stocks and bonds, to diversify away from reliance on oil (Montambault-Trudelle, 2023). The GPFG later followed this pattern, using Norway's oil and gas revenues to invest in over 9,000 companies worldwide (NBIM, 2024). This focus on commodity-driven wealth highlights why early SWFs prioritized stability and savings, shaping their performance evaluation methods, like the Brinson Hood Beebower (BHB) model used in this study.

Another key aspect of SWF history is its role in economic stabilization. Initially, the literature indicates that early SWFs were mostly designed to smooth out economic fluctuations caused by volatile resource prices. For instance, KIA and ADIA invested oil surpluses during boom years to create buffers for economic downturns, such as the 1970s oil crisis or the 2008 crisis (Montambault-Trudelle, 2023).

In a similar manner, the GPFG was established to protect Norway's economy from oil price fluctuations, with NBIM managing investments to ensure steady returns (NBIM, 2024). This stabilization objective initially led to conservative investment strategies, characterized by significant allocations to low-risk fixed-income assets, followed later by a gradual shift toward equities, which are key to this thesis's analysis of GPFG's performance during crises.

The spread of SWFs beyond commodity-based economies marks a second phase of their evolution. Aizenman and Glick (2009) argue that the 2000s were a pivotal period that saw a surge in SWFs driven by trade surpluses and foreign exchange reserves, particularly in East Asia. Funds like Singapore's Government of Singapore Investment Corporation (GIC, 1981) and China's China Investment Corporation (CIC, 2007) were established to manage accumulated reserves, focusing on strategic investments and economic development. Aizenman and Glick (2009) emphasize that these non-commodity SWFs changed the main objectives of SWFs, introducing goals like the industrial policy and global influence, distinct from the GPFG's intergenerational savings mandate. This shift, alongside a sharp increase in the number of SWFs, can raise some concerns that the pursuit of global influence through SWFs may intensify geopolitical tensions, as states leverage these funds to advance national agendas in competitive international markets.

A third aspect of SWFs evolution is their increasing complexity and global impact. Bernstein, Lerner, and Schoar (2013) document how SWFs have shifted from being passive investors to active participants in global markets, engaging in direct and active investments, private equity, and real estate. This transition reflects a broader trend where SWFs, particularly in emerging economies, seek higher returns and strategic influence through active portfolio management. In contrast, Kotter and Lel (2011) suggest that SWFs still resemble passive institutional investors in their investment preferences, targeting firm characteristics similar to those chosen by institutional shareholders, where announcements of SWF investments often lead to short-term increases in stock prices, their long-term effects on firm performance and corporate governance tend to be limited. This duality in SWF behavior, which can be described as active in strategy yet passive in long-term impact, highlights their complexity as well as evolving role in global finance.

In these matters, NBIM acts as an active investor on behalf of the GPFG. In 2024, it voted at 11,154 shareholder meetings, expressing its views to promote long-term value creation and safeguard the fund's assets (NBIM, 2024). This level of engagement is also shared by several other large institutional investors from countries such as the UK, the USA, Canada, and Australia. Notably, the most active institutional investors tend to be pension funds rather than sovereign wealth funds, partly because their investment performance is directly tied to a limited number of beneficiaries' outcomes.

As of 2024, the growing number of SWFs, now exceeding 100 globally (SWF Institute, 2024), underscores their rising influence. This literature together suggests that SWFs are navigating a complex interaction of need for economic returns and state interests, shaping their strategies in an increasingly interconnected and competitive global market environment. For instance, GPFG recently expanded its portfolio to include real estate in 2010 and unlisted infrastructure in 2023, reflecting a broader trend among SWFs to diversify beyond the traditional spectrum of equities and fixed income (NBIM, 2024). Bernstein, W. J., Lerner, J., & Meier, I. (2013) highlight that the shift to these strategies, in particular, asset categories like private equity and real estate often face scalability issues, which can make sustaining these strategies more difficult as the fund expands.

This increases the complexity of performance measurement, as SWFs such as the GPFG must navigate volatile markets, such as those during the 2008, 2020, and 2022 crises, which tested their asset allocation and selection strategies.

The historical development of SWFs, from commodity-driven funds to sophisticated global investors, underscores their diverse mandates and the challenges of evaluating their performance. Rozanov (2005) provides an initial perspective on their origins, while Aizenman and Glick (2009) estimate the factors necessary for their emergence, and Bernstein et al. (2013) highlight their growing complexity, setting the stage for discussing the GPFG's governance, attribution models, and crisis responses. The historical focus on commodity wealth and stabilization shaped SWF mandates, including the GPFG's emphasis on intergenerational savings. Aizenman and Glick (2009) show how early SWFs laid the groundwork for modern funds and their development, with the GPFG building on their model by investing globally while maintaining a high degree of transparency under the Santiago Principles (IFSWF, 2008). This evolution helps investigate how GPFG generates its excess returns and whether its benchmark adapts to turbulent markets, bridging historical context with modern financial analysis.

2.2 Transparency standards in sovereign wealth funds

SWF transparency standards are made to ensure accountability and alignment with national goals outside of financial performance, which is a major development in their global approval. Frameworks like the Santiago Principles guide funds like the GPFG. Rather than operating in privacy, the GPFG has become a worldwide model of transparency, publishing detailed quarterly and annual reports, voting records, and ethical exclusion lists. This commitment reflects broader international concerns regarding the governance and legitimacy of sovereign investors, and aligns with its efforts to balance ethics, ESG risks, and returns (Halvorssen, 2023).

Truman (2008) provides a comprehensive framework for sovereign wealth fund best practices aimed at enhancing transparency, predictability, and accountability, not only to their citizens and governments but also to host countries and financial market participants. His framework is based on a scoreboard evaluating 44 SWFs based on 33 elements grouped into four main categories: fund structure, governance, transparency and accountability, and portfolio management behavior. Importantly, these best practices do not require any fund to adopt other measures beyond those already implemented by at least one peer fund, ensuring feasibility and realism.

From a more logical perspective, while such frameworks improve global trust and cooperation by increasing transparency and reducing uncertainty about SWF intentions, they may also impose operational constraints on SWFs. A recent example would be during the 2022 Ukraine War, as revealing investment strategies or shifts in asset allocations might have led to front-running by other market participants or intensified political pushback from host countries concerned about their national interests. Thus, one can conclude that although transparency fosters legitimacy and accountability, it may also reduce strategic flexibility and competitive advantage, especially in volatile or politically sensitive environments.

The rise of SWF transparency standards also raised many concerns about their market influence. As SWFs expanded, reaching over $13 trillion by 2024 (SWF Institute, 2024), policymakers and scholars feared potential economic biases. Megginson and Gao (2020) highlight that the rapid growth and strategic nature of SWF investments raised the alarm over their transparency and political neutrality. In contrast, Stone and Truman (2016) recently published their fourth sovereign wealth fund scoreboard, assessing the transparency and accountability of 60 SWFs. While transparency levels vary significantly among funds, their analysis of changes over time indicates a general trend of improvement in SWF transparency. To further address these general concerns, the Santiago Principles were adopted in 2008 (IFSWF, 2008), outlining 24 voluntary guidelines to promote disclosure, accountability, and sound governance. GPFG complies by regularly publishing detailed reports on its 70% equity, 27% fixed-income, and 3% real estate allocations, increasing investor trust during the post-2008 recovery period (NBIM, 2009). These standards not only legitimize SWFs but also provide a stable framework for performance attribution using models like Brinson-Hood-Beebower (BHB).

Seen through a legal lens, the Santiago Principles reflect a different form of ‘soft law’. Rather than strict, binding legal frameworks, soft law is expressed through standards, rankings, and monitoring frameworks, which exist outside of state and international regulatory enforcement. Compliance with these standards, inclusion in rankings, and implementing monitoring frameworks, in principle, gives membership in a “club”. Soft law works through socialization and normative pressures in place of direct intimidation and threats of legal sanctions. For sovereign wealth funds, adherence to the Santiago Principles and membership in the International Forum of Sovereign Wealth Funds (IFSWF) provides a seal of approval that the fund (and by extension the government owner) is committed to transparency and disclosure in keeping with the norms of institutional investment management. Membership also holds the fund accountable to its peers for good practice, as bad practice reflects across sovereign wealth funds as a group. For example, the collapse of Malaysia's 1 Malaysia Development Berhad (1MDB) while being caught in a major scandal had a large impact across Asia, generally fostering negative perceptions of sovereign wealth funds in the region (Vittori & Kumar, 2024).

In Europe, the EU's 2008 communication urged transparent practices, shaping GPFG's rigorous oversight by the Ministry of Finance (European Commission, 2008). This transparency supports the Fama-French factor analysis, as open data ensures precise exposure calculations, especially during crises such as the 2022 Ukraine War's disruptions.

Ethical investment guidelines further distinguish SWFs like the GPFG. Truman (2008) highlights GPFG's exclusion of companies violating environmental or human rights standards, guided by Norway's ethical council. This approach, strengthened after 2008, aligns with the common European values and enhances the GPFG's reputation, impacting its performance attribution by prioritizing sustainable returns (NBIM, 2024).

2.3 Evolution of Sovereign Wealth Funds

SWFs have evolved over the years from commodity-driven Investment vehicles to more diverse, active investors, navigating increasingly complex regulations and adopting newer technologies. GPFG clearly reflects this shift, diversifying and expanding its scope of investment into real estate and infrastructure over the years. (NBIM, 2024).

Non-commodity sovereign wealth funds emerged later in the 2000s, during the peak of industrialization in certain countries, driven by the accumulation of excess foreign currency reserves resulting from sustained trade surpluses. Examples include Singapore's Government of Singapore Investment Corporation (GIC) and China's China Investment Corporation (CIC), which invest the national reserves to achieve their strategic objectives. These funds tend to improve the financial performance of already well-performing domestic firms but are found to have a limited impact on underperforming ones, according to Nguyen, Nguyen, and Elgammal (2021). Additionally, while they may enhance non-financial performance when it is initially weak, their presence can lead to a decline in social and environmental performance when those aspects are already strong. This suggests that non-commodity SWFs prioritize financial outcomes, strategically balancing other objectives to maintain or enhance returns. Reisen (2008) distinguishes between commodity-funded and non-commodity-funded SWFs, highlighting that non-commodity SWFs, primarily found in East Asian countries, mainly serve as a mechanism to manage excess savings and stabilize national economies. His study also cautions against protectionist policies toward SWF investments, emphasizing their important role in global financial markets and the potential negative economic consequences if host countries limit their activities.

The role and strategies of sovereign wealth funds evolved significantly after the global economic crisis of 2008, significantly helping increase global attention on them due to their relatively stable funding sources, often derived from natural resources and commodities. The rise in commodity prices before the crisis allowed many commodity-exporting countries' SWFs to accumulate a significant amount of assets. These funds tend to follow cyclical investment patterns: during periods of economic growth and excess liquidity, they often increase investments, but when crises occur, their funding sources can decline sharply. This cyclical behavior is evident in both the Global Financial Crisis (GFC) and the COVID-19 pandemic (Al-Sadiq & Gutiérrez, 2023).

Despite these challenges, SWFs are rarely at risk of failure or liquidation. Stabilization funds, in particular, play a critical role in reducing government spending during economic downturns, which shows that SWFs have a strong local impact in addition to their international investment activities. The stabilization role comes largely from the need to reduce government revenue volatility in economies that are heavily dependent on exports of a single commodity, usually oil or natural gas. However, with growing volatility in energy markets, the reasoning now is for SWFs to transform energy assets into long-term financial assets and to reduce the impact of commodity price shocks on the domestic economy. It is worth noting that the existence of a stabilization SWF alone does not guarantee protection against commodity price volatility, as these funds cannot fully replace a rigorous fiscal policy (Boubakri, Fotak, Guedhami, & Yasuda, 2023).

In response to a growing economic uncertainty, many SWFs have adapted by enhancing their risk management and further diversifying their portfolios. By 2013, SWF assets were projected to grow from $2 trillion to between $3.4 trillion and $5.8 trillion, highlighting their growing influence in global finance, even in times of crisis (IMF, 2010). Today, the industry's assets exceed $13 trillion and continue to attract attention and new participants, with potential entrants including the United States of America under President Trump's second administration.

Active investment strategies are becoming increasingly important in light of the evolving nature of sovereign wealth funds. Bortolotti et al. (2015) provide interesting evidence that SWFs shifted from passive asset allocation to active strategies and engagement, notably in public equity investments, which had been almost exclusively in passive investments prior, while now increasing their engagement in private sector direct investment, particularly diverse area of private equity (Monteiro, 2023). Bernstein et al. (2013) found that SWFs follow particular trends in their investments, allocating funds into domestic markets during overvaluations of asset markets and directing their allocations internationally when foreign investments are overvalued. The involvement of politicians in management roles also means greater allocation towards domestic investment as opposed to institutions with other managers internationally allocating the capital to limit clients' "home country bias" (Bernstein et al., 2013). The Government Pension Fund Global is a prime example of a SWF engaging in corporate governance through voting rights and management (NBIM, 2024). However, active investing presents many governance challenges, as highlighted by Bortolotti et al. (2015), who identify a phenomenon known as the "sovereign wealth fund discount." This discount reflects the market's tendency to assign lower valuations to firms receiving SWF investments, particularly when those funds take significant ownership stakes or actively engage in corporate governance. The study suggests that such discounts arise from investor concerns about political influence, limited transparency, and the potential for non-commercial objectives to interfere with firm performance, all of which can adversely impact the long-term value of the firm.

Sovereign wealth fund investments are associated with statistically significant declines in various performance metrics for target firms compared to matched private-sector investments. Over three years following the investment, Bortolotti et al. (2015) find that SWF-backed firms experienced substantial decreases in return on assets, sales growth, and market-to-book ratios. For example, sales growth declined by 8.89 percentage points over three years, and the return on assets fell by 2.63 percentage points relative to matched peers. These findings are consistent with both the political agenda and passive investor hypotheses, which suggest that SWFs may prioritize non-commercial objectives or exert limited oversight, thereby impacting firm performance. Additionally, while both SWF-backed and private-sector firms showed some improvement in liquidity (quick ratio), the differences were not statistically significant. Notably, leverage, as measured by the debt-to-assets ratio, declined significantly for SWF-backed firms relative to their counterparts, pointing to more conservative capital structures.

These empirical results support the notion that active SWF investments can trigger market skepticism and performance challenges in target firms, and that the use of more active investment strategies during market stress, such as the COVID-19 pandemic, or periods of geopolitical tensions such as the Ukraine war shows the considerable need for a robust risk practice to moderate strategic influence and portfolio risk. By 2024, GPFG held equity stakes in over 9,000 companies globally, reflecting its significant influence amid global market volatility (NBIM, 2024).

Performance Metric (Mean Change Relative to Year Prior to Investment)	Year	SWFs (1)	Matched Sample (2)	Difference-in-Differences (1)-(2)	Obs
Return on Assets	1	-2.31%*** (-3.70)	-0.63% (-0.70)	0.0247	517
	2	-1.13%** (-1.97)	5.88%*** (5.14)	-7.01%*** (-5.59)	445
	3	-1.76%** (-2.40)	0.87% (0.62)	0.0444	266
Sales Growth	1	-8.63%*** (-3.82)	-0.28% (-0.25)	-8.35%*** (-3.19)	284
	2	-12.17%*** (-5.84)	11.32%*** (7.15)	-23.49%*** (-8.92)	360
	3	-8.89%*** (-3.76)	3.42%** (2.27)	-12.31%*** (-4.49)	189
Market-to-Book Ratio	1	-0.63 (-6.63)	0.04 (0.22)	-0.67** (-5.59)	496
	2	-1.32*** (-4.98)	-0.31** (-2.10)	-1.01*** (-3.37)	430
	3	-1.33*** (-3.40)	-0.72*** (-3.34)	-0.61 (-1.36)	261
Quick Ratio	1	0.25** (2.03)	0.35** (2.48)	-0.10 (-0.52)	350
	2	0.14* (1.66)	0.37** (2.34)	-0.23 (-1.30)	305
	3	0.06 (0.57)	-0.07 (-0.53)	0.13 (0.75)	169
Debt to Assets	1	-0.22% (-0.34)	5.29%*** (7.47)	-5.51%*** (-6.23)	631
	2	-0.72% (-1.07)	4.98%*** (6.62)	-5.71%*** (-5.99)	490
	3	-0.94% (-1.13)	1.81%** (2.16)	-2.75%** (-2.31)	426

Table 2: Impact of SWF Private Investments on Firm Performance – Adapted from Bortolotti et al. (2015)

Notes: *** p<0.01, ** p<0.05, * p<0.1. t-statistics are in parentheses. SWFs (1) represents firms with SWF investments; Matched Sample (2) represents non-SWF-invested firms. Difference-in-Differences is calculated as (1)-(2).

Technological advancements also contribute to developing SWF management, as SWFs have evolved into more professionalized and sophisticated investors, increasingly adopting modern risk management tools. NBIM, for instance, has reported using complex algorithms and real-time data systems to monitor portfolio risks (NBIM, 2024). This supports precise attribution of the performance, as technology enables detailed performance tracking across crises.

2.4 Types of Sovereign Wealth Funds and their objectives

Sovereign wealth funds share fundamental characteristics between themselves such as state ownership, long-term investment horizons, diversified portfolios, and a centralized governance system. While some are independently managed under a mandate, oversight is often provided by a central authority. And despite these shared features, SWFs differ significantly in their objectives, financing structures, and investment approaches.

Unlike traditional institutional investors such as pension or endowment funds, where future liabilities are known in advance and guide a fixed, long-term investment strategy, SWFs face a more complex structuring process. For the sake of comparison, traditional funds follow a linear investment model, as the timing and magnitude of liabilities are predetermined. This allows for straightforward optimization of asset allocation and risk management. As Fatemi et al. (2011) explains, The structure typically follows:

1. Define liabilities → 2. Design and establish the fund → 3. Accumulate and manage assets

First, defining liabilities involves identifying the financial obligations or investment objectives the fund aims to meet, such as generating returns for retirees in a pension fund, providing income for mutual fund investors, or achieving capital growth for private investors. This step requires assessing the scale, timing, and risk profile of these obligations to set the fund's purpose, whether it is income generation, capital appreciation, or risk diversification, guiding its investment strategy and horizon. For example, a pension fund may define liabilities as future payouts to retirees, requiring a long-term, stable return profile. Second, designing and establishing the fund involves creating its legal, governance, and operational framework. This includes drafting legal documents (e.g., a prospectus or trust agreement), defining governance structures (e.g., fund managers, oversight boards), setting investment policies (e.g., asset allocation, risk limits), and determining the funding sources, such as investor contributions or institutional capital. Strong governance is essential to ensure transparency and accountability, minimizing risks like mismanagement that can erode investor confidence and returns. Finally, accumulating and managing assets involves raising capital from investors (e.g., through subscriptions or institutional commitments) and managing the portfolio to achieve the defined objectives. This includes investing in assets like stocks, bonds, or alternative investments and actively monitoring performance to balance risk and return, particularly during market volatility.

By contrast, SWFs, and particularly those funded through commodity revenues, have to manage unpredictable and often volatile revenue streams. As Fatemi et al. (2011) explain, this requires a flexible, circular approach to fund structuring. Because revenues can spike or drop dramatically depending on global commodity prices, asset accumulation often precedes formal fund setup and the definition of long-term objectives. The process may repeat with each economic cycle, adapting to evolving fiscal conditions:

1. Accumulate assets → 2. Design and establish the fund → 3. Define liabilities → 4. Restructure as needed

First, accumulating assets involves gathering initial capital, typically from national revenue sources such as commodity exports (e.g., oil or gas revenues for funds like Norway's Government Pension Fund Global), fiscal surpluses, or foreign exchange reserves. This step ensures the SWF has sufficient resources to begin its operations, setting the stage for its investment activities. Second, designing and establishing the fund involves creating its legal, governance, and operational framework. This includes implementing legislation to formalize the fund, defining governance structures (e.g., independent boards, transparency protocols), and setting investment policies, such as allowed asset classes (e.g., public equity, private equity) and risk limits. Strong governance is crucial to mitigate political interference, which can lead to market skepticism and reduced firm valuations, as observed in studies where SWF-invested firms underperform in metrics like sales growth or profitability. Third, defining liabilities involves identifying the financial obligations or economic objectives the SWF aims to address, such as funding future pension payments, stabilizing fiscal budgets against commodity price volatility, or preserving wealth for future generations. This step clarifies the fund's purpose, whether stabilization, savings, or development, guiding its long-term strategy and risk profile. For instance, a fund may prioritize stable returns to cover future possible fiscal deficits in a resource-dependent economy. Finally, restructuring as needed requires periodically reassessing and adjusting the fund's strategy, governance, or asset allocation in response to changing economic conditions, market volatility (e.g., during crises like the COVID-19 pandemic), or performance challenges.

The main distinction between the two timelines for establishing a fund lies in the sequencing of the third and fourth steps and their emphasis. The three-step timeline prioritizes defining the fund's financial obligations first to set its strategic purpose, followed by governance design and asset management. In contrast, the four-step timeline begins with accumulating assets, reflecting scenarios where capital (e.g., oil revenues) is collected before formalizing the fund's structure or objectives, and adds a final restructuring step to emphasize ongoing adaptability to economic or market changes, which provides a more flexible, iterative framework.

This distinction is crucial to understanding the evolution and operational diversity of SWFs. Their dynamic funding environment requires an adaptive governance framework and flexible investment policies, especially in resource-rich economies subject to external shocks.

A widely accepted classification by Mehrpouya, Huang, & Barnett (2011) categorizes SWFs based on their liability structures and objectives into six types. The four most commonly observed types are detailed below

2.4.1 Stabilization Funds

Stabilization funds are mainly set up to protect national budgets from commodity price volatility, especially in resource-rich economies. They accumulate reserves during boom periods and use them during downturns, helping smooth fiscal revenues. These funds prioritize liquidity and typically invest in low-risk assets like sovereign bonds and foreign currency reserves. For example, the Russian Reserve Fund, discontinued in 2018, played a crucial role in mitigating fiscal shocks. As Al-Sadiq and Gutiérrez (2023) highlight, these funds help prevent procyclical fiscal policies, such as increasing spending during booms and cutting it during recessions, which could otherwise exacerbate economic instability.

2.4.2 Intergenerational Wealth Transfer Funds

Intergenerational wealth transfer funds aim to convert the temporary revenues from non-renewable resources into sustainable, long-term wealth for future generations. Their investment approach focuses on intergenerational justice, ensuring that today's resource wealth is preserved in a financial form for tomorrow's citizens.

These funds are typically more risk-tolerant, with strategic allocations to global equities, real estate, and alternative investments. Examples include Norway's Government Pension Fund Global and the Kuwait Investment Authority (KIA). These funds aim to convert the revenues from limited resources into financial assets that can generate returns for future generations. GPFG, in particular, is well-known for its resilience during global financial crises, which is strong evidence of its robust long-term approach that balances risk with sustainable returns. However, while past performance suggests this method´s resilience, this study will assess in detail the robustness of such funds under modern market conditions, using updated and thorough analytical techniques.

2.4.3 Reserve Investment Corporations

Reserve investment corporations are designed to manage surplus foreign exchange reserves, with the goal of achieving higher returns than traditional, safer, and low-yield instruments such as government bonds. Unlike central bank reserves held solely for liquidity, these funds follow more aggressive investment strategies, including allocations to global equities, private equity, and infrastructure.

China Investment Corporation (CIC) and Singapore's Government Investment Corporation (GIC) are leading examples. These funds must keep a delicate balance between optimizing the returns and ensuring the availability of liquid capital. Their dual mandate makes governance and risk management more complex to integrate. While they share some long-term objectives with intergenerational funds, reserve investment corporations must remain highly reactive to short-term liquidity needs.

2.4.4 Contingent Pension Reserve Funds

Contingent pension reserve funds are established to meet long-term pension obligations and manage demographic challenges such as population aging. These funds typically invest in a balanced mix of growth-oriented assets like equities and safer assets like government bonds. Their primary objective is to accumulate wealth today to cover future public pension liabilities.

France's Pensions Reserve Fund (FRR) is a key example of a contingent pension reserve fund (CPRF). CPRFs are designed to act as long-term financial buffers, setting aside funds for future pension liabilities without having direct current beneficiaries. Unlike traditional pension funds, which manage assets to meet immediate or near-term payouts to retirees, CPRFs are set up exclusively to mitigate future fiscal pressures, such as those arising from demographic aging.

Essentially, these funds are also distinct from traditional sovereign wealth funds. While SWFs typically serve broad macroeconomic purposes (e.g., stabilizing commodity revenues or saving wealth for future generations), CPRFs have a specific mandate: to support public pension systems. Their assets are often legally kept for pensions and cannot be repurposed for other state spending. This functional specificity, combined with their lack of current beneficiaries, places CPRFs in a unique category between pension funds and SWFs.

2.5 The role of good governance in managing the objectives of sovereign wealth funds

It is important to note that many SWFs do not simply fall into a single category. Some funds have hybrid functions, simultaneously pursuing stabilization, savings, and development goals depending on their evolving mandates and national needs. And managing multiple objectives requires an effective governance framework, clearly defined mandates, and a transparent reporting structure.

This good governance structure ensures that no single objective overwhelms the others, and that the fund's strategy remains consistent with its core mission. In a similar way, benchmark selection must accurately reflect the fund's diversified goals. Transparency, accountability, and institutional independence are extremely critical for maintaining legitimacy and public trust.

The table below summarizes the key distinctions between the four primary types of SWFs discussed:

Type of Fund	Primary Objective	Funding Source	Typical Asset Allocation	Example
Stabilization Fund	Smooth fiscal revenues; mitigate commodity price shocks	Commodity export surpluses	Liquid, low-risk assets (e.g., bonds, FX reserves)	Russian Reserve Fund
Intergenerational Wealth Fund	Save wealth for future generations	Resource windfalls	Long-term, risk-tolerant (e.g., equities, RE)	GPFG, KIA
Reserve Investment Corporation	Enhance returns on excess reserves	Foreign exchange reserves	Risky and diversified (e.g., PE, infrastructure)	CIC, GIC
Contingent Pension Reserve Fund	Offset future pension liabilities	Budget allocations	Balanced: growth & defensive assets	Australia's Future Fund

Table 3: Main types of Sovereign Wealth Funds – Adapted from Mehrpouya, Huang, & Barnett (2009)

Another way to define sovereign wealth funds would be by their funding sources, distinguishing them between commodity and non-commodity SWFs. Commodity SWFs, established in resource-rich countries like Norway or the UAE, are funded by revenues from limited resources such as oil or gas, aiming to transform finite wealth into sustainable financial assets. These funds choose between using the resources now or saving them for the future, while being guided by economic principles like the Hotelling Rule, which balances retaining resources against investing proceeds, and the Hartwick Rule, which promotes reinvesting revenues to preserve national wealth (OECD Development Centre, 2008). Restrictions on foreign investments, however, can lower returns, potentially increasing commodity prices or fostering domestic mismanagement.

On the other hand, non-commodity SWFs, more frequent in East Asian countries like China or Singapore, are mostly financed through foreign exchange reserves or trade surpluses, often driven by high savings from undervalued currencies or mandatory savings programs. These funds help correct imbalances caused by too much investment, when the amount of capital being built up grows faster than the income it generates, resulting in low returns, as seen in Singapore's Central Provident Fund with a 1.2% real return (OECD Development Centre, 2008). Unlike commodity SWFs, typically focused on intergenerational equity or stabilization, non-commodity SWFs prioritize managing surplus reserves and mitigating currency or interest rate risks. This distinction underlines the diverse economic roles and governance challenges SWFs face, highlighting the need for custom strategies to ensure long-term financial stability.

2.6 Governance and Management in Sovereign Wealth Funds

2.6.1 Governance Structures of Sovereign Wealth Funds

Stakeholder engagement is a key feature that distinguishes the GPFG's governance approach. As Norges Bank Investment Management maintains close consultations with Norway's Parliament (Storting) through regular reporting submissions to the Ministry of Finance, ensuring a high level of transparency and accountability. For example, NBIM's 2008 consultation response on ethical guidelines illustrates this engagement during the recovery from the financial crisis (NBIM, 2008). This parliamentary oversight enhances the trust and legitimacy in the fund's management. In contrast, Singapore's sovereign wealth fund (GIC) emphasizes transparency through detailed public reporting of its strategies and risk management (GIC Private Limited, 2020). However, unlike the GPFG, the GIC's engagement with the public institutions does not involve parliamentary oversight but is primarily through government ministries. This distinction reflects different governance frameworks, which influence how each fund manages stakeholder accountability, especially during crises such as the 2008 GFC or the 2020 pandemic.

2.6.2 General Governance Models in Sovereign Wealth Funds

Comparing the GPFG's management and governance with other prominent SWFs highlights its unique approach, which shapes its performance attribution framework. As the GPFG's governance integrates oversight and ethics. Clark & Monk (2010) emphasize that the GPFG gets its legitimacy from a strong commitment to procedural justice, including transparency, ethical screening, and responsible investment. This governance model not only reinforces public trust but also influences the way performance is measured, aligning financial outcomes with long-term societal values. Unlike GIC's market-driven approach, which prioritizes maximizing financial returns often without a clear ethical framework (Norges Bank Investment Management, 2009; GIC Private Limited, 2020). Similarly, ADIA shows limited transparency, with minimal board disclosure and limited public information, restricting the ability to assess the performance decisions, especially during market crisis, compared to GPFG's overall more open governance structure as seen during 2022's market volatility (Norges Bank Investment Management, 2022; Abu Dhabi Investment Authority, 2015). Truman (2008) provides important context by noting that only a few sovereign wealth funds officially commit to guidelines on corporate responsibility and ethical investment, particularly, just about 30% of all SWFs. He highlights the GPFG as a leading example among non-pension SWFs that not only adhere to these guidelines but also actively incorporate ethical considerations into their investment policies. This includes explicit restrictions on investments in certain sectors or countries and transparent reporting on governance and ethical standards. Such a model helps foster greater public trust and aligns fund management with broader societal values, which is particularly important for a fund like GPFG that manages national wealth on behalf of future generations. The adoption of ethical frameworks and high transparency standards ensures that the fund's allocation decisions are not only financially sound but also socially responsible.

2.6.3 The Santiago Principles

The Santiago Principles are a set of 24 generally accepted guidelines designed to promote transparency, good governance, accountability, and prudent investment practices among sovereign wealth funds as well as keep a stable global financial system, according to the IFSWF. Developed in 2008 with the help of the International Working Group of Sovereign Wealth Funds, these principles provide a global framework that ensures that SWFs operate with clear objectives, sound risk management, and ethical standards. By adhering to these principles, funds like the GPFG reinforce public trust and enhance their reputation as responsible long-term investors.

One principle that is particularly relevant to the theme of this thesis is GAPP 23, which emphasizes the importance of consistent measurement and transparent reporting of investment performance, both in absolute terms and relative to benchmarks. According to this principle, sovereign wealth funds should adopt clearly defined standards to assess and report their investment outcomes. This practice is fundamental to an effective performance attribution, as it enables fund managers to evaluate whether investment decisions align with the strategic goals and risk models. Moreover, reliable performance measurement facilitates accountability and enables comparisons with benchmark portfolios, which is essential to understanding the effectiveness of allocation and active management decisions. In the case of Norway's GPFG, compliance with GAPP 23 strengthens the credibility of its performance reporting and provides a solid foundation for both the BHB attribution framework and factor-based analytical frameworks.

2.6.4 Governance in The Government Pension Fund Global

The Government Pension Fund Global was first established in 1990 by the Norwegian Parliament (Storting) under the name Norwegian Government Petroleum Fund (GPF) through an act of national legislation (Backer, 2009). The fund's initial capital was primarily sourced from revenue generated by the sale of newly discovered oil and gas resources. The main objective of the GPFG was to ensure that the wealth derived from these finite natural resources would not change Norway's economy or society in a negative way, while ensuring that the financial benefits are preserved for future generations, who would not directly profit from the immediate sale of these commodities.

In 2006, the fund was renamed the Government Pension Fund Global and has since become known as the most transparent sovereign wealth fund worldwide. This high level of transparency has facilitated wide data availability through its publicly accessible reports and databases. As of December 2024, the GPFG's value reached a record-high 19.742 trillion Norwegian kroner (approximately $1.7 trillion), making it the largest sovereign wealth fund globally in terms of assets under management. This growth is attributed to a combination of robust investment performance, substantial capital inflows, and a favorable currency exchange rate, a status largely attributable to its exceptional governance framework and prudent investment strategy. (Norges Bank Investment Management, 2024)

This broad investment strategy underscores NBIM's commitment to achieving the highest possible return after costs, within the constraints imposed by the mandate from the Ministry of Finance. By integrating both passive and active management strategies across different asset classes, NBIM aims to safeguard and develop the GPFG for the benefit of future generations.

The GPFG's governance framework is characterized by its transparency, accountability, and ethical investment practices. The Norwegian Parliament (Stortinget) sets the principal legal framework through the "Government Pension Fund Act,", effective since January 01, 2020, which outlines the fund's objectives and guidelines. The Norwegian Parliament has formally entrusted the Ministry of Finance with the responsibility of managing the GPFG. However, the day-to-day operational management is delegated to Norges Bank, Norway's central bank. This division creates a multi-layered governance system where three main bodies work collaboratively to oversee and direct the fund's activities (Norges Bank Investment Management, n.d).

The Ministry of Finance issues an investment mandate that defines the GPFG's overall investment strategy, risk management framework, reporting obligations, and responsible investment guidelines. All decisions concerning the fund's management and the provisions in this mandate require approval by the Parliament (Storting).

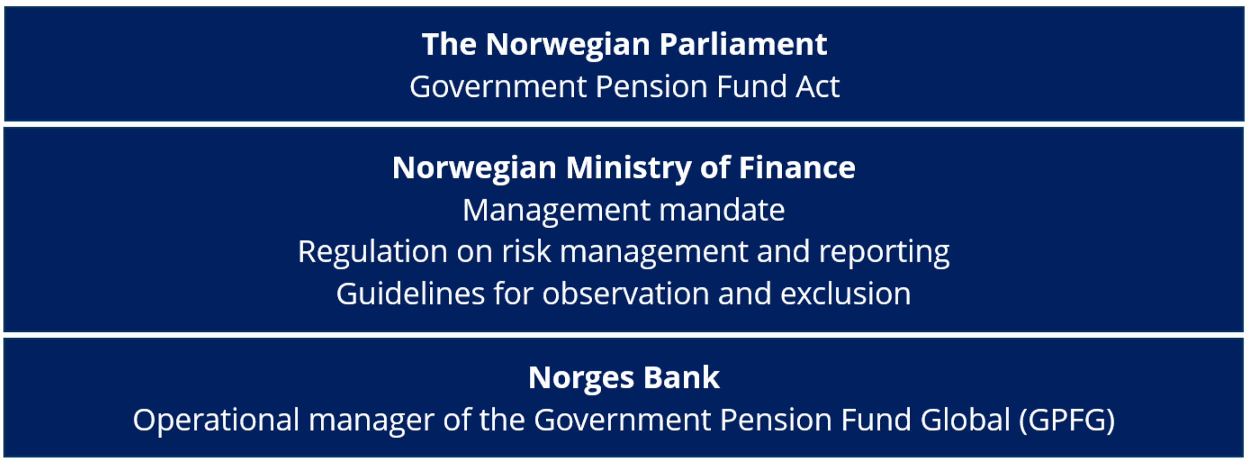

Figure 1: Hierarchy of oversight, management, and delegation of authority within the GPFG (from Ministry of Finance, 2021)

According to the Norwegian Ministry of Finance, the GPFG operates under a clear and robust governance framework that ensures transparency, accountability, and effectiveness throughout its management processes. This framework involves multiple oversight layers and control mechanisms aimed at preserving the fund's long-term financial stability and maintaining public trust. Five key actors are central to the governance of the GPFG:

2.6.4.1 The Norwegian Parliament (Stortinget)

As the highest authority, the Parliament establishes the legal foundation for the GPFG through the "Government Pension Fund Act." It defines the fund's main purpose and guidelines, ensuring alignment with Norway's long-term financial interests and ethical standards.

2.6.4.2 The Ministry of Finance

The Ministry oversees the fund's management by issuing the regulatory framework and management mandate to Norges Bank. This mandate specifies investment guidelines, risk limits, and ethical considerations that must be followed. The Ministry has also appointed an independent Council on Ethics responsible for evaluating investments against environmental, social, and governance (ESG) criteria. This Council recommends exclusions or observations based on the fund's ethical guidelines, reinforcing the fund's commitment to responsible investing.

2.6.4.3 Norges Bank and Its Executive Board

Norges Bank's Executive Board ensures that the GPFG is managed following the Ministry of Finance's mandate. The Board further strengthens its governance by establishing internal policies and guidelines that enhance risk management and compliance. It supervises Norges Bank Investment Management (NBIM), the body directly responsible for investment decision-making.

2.6.4.4 Norges Bank Investment Management (NBIM)

NBIM handles the day-to-day management of the GPFG, executing investment decisions based on an assessment of risk-return trade-offs while adhering to the fund's financial and ethical guidelines. The CEO of NBIM oversees the implementation of investment strategies, operational management, and internal control systems.

2.6.4.5 Internal and external managers of NBIM

Within NBIM, investment management is carried out through a combination of internal teams and carefully selected external managers. The internal teams are responsible for the fundamental strategic functions, including portfolio construction, risk monitoring, and operational control. Meanwhile, external asset managers are engaged to provide specialized expertise, particularly in less liquid markets or asset classes where local presence and experience are essential. This management approach allows NBIM to diversify strategies, enhance performance, and maintain strong governance standards across all investment activities.

The figure below illustrates the detailed governance hierarchy of the Government Pension Fund Global, highlighting the layers of oversight and the delegation of responsibilities among key institutions.

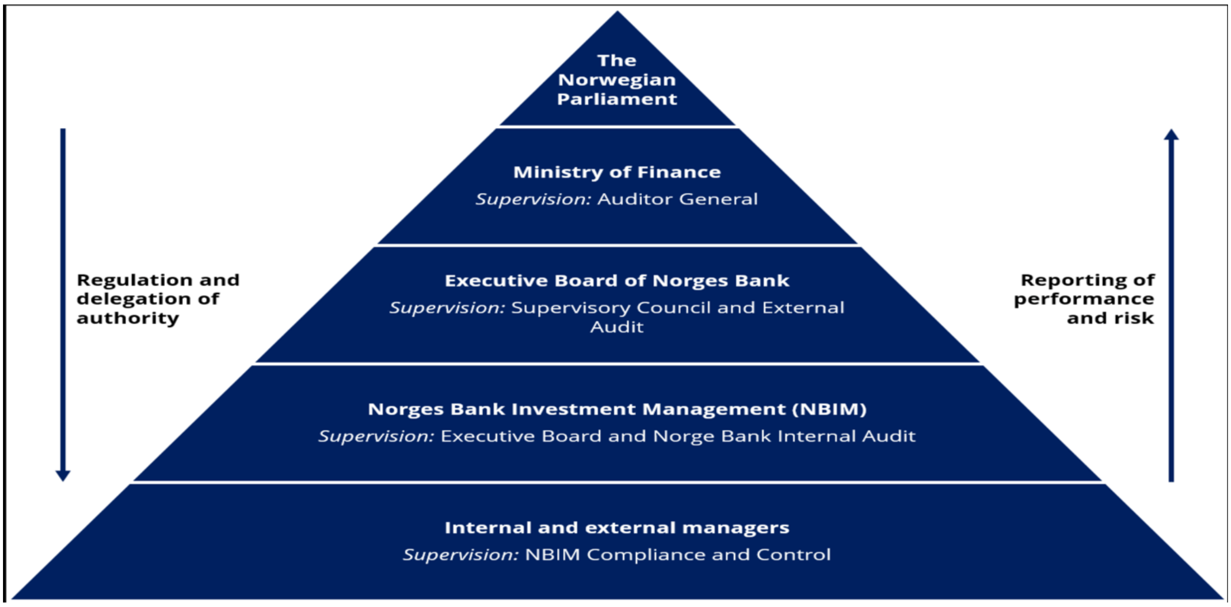

Figure 2: governance and Oversight structure of NBIM (from Ministry of Finance, 2021)

2.7 Sovereign Wealth Funds and Geopolitical Challenges

Sovereign Wealth Funds operate in an increasingly volatile geopolitical landscape. Although originally designed to stabilize economies and preserve wealth, recent global events have revealed in many ways their vulnerability to external shocks and political interference.

Despite the multiple geopolitical challenges impacting SWFs, this study focuses on three pivotal events, 2008, 2020, and 2022, due to their profound effects on SWF performance and strategic operations. The 2008 global financial crisis tested SWFs' resilience, forcing funds like Norway's GPFG to navigate sharp market declines, highlighting the need for diversified portfolios (OECD Development Centre, 2008). The 2020 COVID-19 crisis triggered unprecedented market volatility, severely affecting SWFs' portfolio valuations, particularly for equity-heavy funds, highlighting the importance of robust risk management to mitigate global economic shocks. Finally, the 2022 Russia-Ukraine conflict triggered energy price volatility and sanctions, impacting commodity SWFs' asset valuations and prompting strategic reallocations to mitigate geopolitical risks. These three events underscore the critical interplay between global politics and SWF management, requiring robust governance to balance economic objectives with external pressures.

2.7.1 Historical Context and Geopolitical Realignments

Since the end of World War II, the global political order has undergone multiple transformations. The Cold War era was marked by the formation of NATO in 1949, aimed at deterring Soviet expansion, and the Warsaw Pact as a counterbalance from the soviet side. These developments triggered a heavy arms race, particularly in nuclear weaponry, reinforcing ideological and military divisions. (U.S. Department of State, n.d.)

The oil crisis of 1973 reshaped Western energy policy, increasing their strategic dependence on the Middle East and initiating a broader shift in global economic alliances. The collapse of the Soviet Union and the end of the Cold War led to the emergence of new nation-states and promoted the integration of Europe, ending in the formation of the European Union. All these developments laid the groundwork for an era of economic globalization and relative geopolitical stability.

2.7.2 The 2008 Global Financial Crisis: A Turning Point for SWFs

The 2008 global financial crisis marked a key moment for sovereign wealth funds. As banking systems in the U.S. and Europe collapsed and credit markets froze, SWFs found themselves both vulnerable and, at the same time, unexpectedly influential. Several major funds, particularly from the Middle East and Asia, stepped in to recapitalize struggling Western financial institutions. For instance, the Abu Dhabi Investment Authority and Singapore's GIC made high-profile investments in Citigroup and UBS, respectively. For instance, the GIC invested over £5.5 billion to acquire a 9% stake in UBS; however, the Swiss bank's shares had declined by 46% that year. Additionally, in January, it committed $6.88 billion as part of a $14.5 billion capital injection for the struggling U.S. bank Citigroup (The Guardian, 2008; Truman, 2010). While these investments were initially welcomed, they also raised concerns about foreign state influence in domestic financial systems, leading to increased calls for governance standards and transparency.

The crisis exposed the need for clearer frameworks regulating how SWFs invest abroad, especially when such investments overlap with strategic sectors. It was also an indirect cause leading to the development of the Santiago Principles in 2008, a voluntary code of best practices established by the International Forum of Sovereign Wealth Funds to promote transparency, good governance, and prudent investment practices (Truman & Bagnall, 2011). This event reshaped the global perception of SWFs, positioning them as stabilizers in times of market distress but also highlighting their potential geopolitical weight in international decision-making.

2.7.3 The COVID-19 Pandemic and the Economic Shifts

The COVID-19 pandemic represented one of the most significant global economic shocks since the 2008 financial crisis, with major implications for SWFs. As global markets collapsed in early 2020 due to widespread disruptions in logistics, combined with strict quarantine measures in global markets, many SWFs experienced sharp declines in asset valuations, with a rapid rise in liquidity pressure and unprecedented volatility across multiple asset classes. According to the International Forum of Sovereign Wealth Funds, several funds were called upon by their governments to support national budgets, healthcare systems, and economic stimulus packages, thus shifting their role from long-term stabilizers to emergency liquidity providers (IFSWF, 2021). The COVID-19 pandemic also caused an unprecedented global economic slowdown, severely disrupting supply chains, collapsing commodity prices due to lower demand, and forcing many economies into a recession. For sovereign wealth funds, especially those reliant on oil revenues like the GPFG, ADIA, and the KIA, the economic shock triggered difficult trade-offs to make. Governments often turned to these funds to cover budget deficits and support emergency spending, which led to substantial withdrawals from reserves, as governments withdrew over $211 billion to support national economies. Despite these challenges, many SWFs capitalized on market dislocations, investing in undervalued assets and benefiting from the subsequent market recovery in 2022, which led to considerable growth in assets under management. (Boubakri et al., 2023; López, 2023)

Moreover, the sharp volatility in global financial markets put great pressure on asset allocation strategies and forced some funds to revise their risk management approaches. In particular, funds with high exposure to equities or real estate saw steep short-term losses, which encouraged a renewed focus on diversification and liquidity. The pandemic also underscored the importance of long-term resilience over short-term gains, supporting the value of ethical and sustainable investment mandates that had already been adopted by funds like the GPFG (OECD, 2021).

During the COVID-19 pandemic, other sovereign wealth funds also suffered a significant decline in asset values, with estimated losses reaching nearly 20% of their assets under management, equivalent to over $800 billion in paper losses. The severity of the impact varied across funds. Those with substantial liquid reserves were better positioned to take advantage of market distress, enabling them to diversify and purchase discounted assets without being forced into distressed sales. Equally, the funds that had to reallocate significant capital to address domestic budgetary needs faced considerable losses as they liquidated holdings under unfavorable market conditions (Bortolotti, Fotak, & Hogg, 2020).

2.7.4 The War in Ukraine and Its Impact on SWFs

The 2022 Invasion of Ukraine by Russia marked yet another turning point in modern geopolitics, with broad implications for global financial markets and SWFs. Following earlier tensions dating back to the 2014 annexation of Crimea and the failure of the Minsk Agreements, Russia's military operation reignited security concerns across Europe and triggered a wide range of sanctions by Western democratic nations. These sanctions, including the freezing of approximately $300 billion in Russian central bank reserves, set a powerful precedent that reverberated across the SWF landscape. (Reuters, 2022)

The war in Ukraine introduced significant economic disruptions that suddenly increased global inflation and intensified volatility in commodity markets, particularly in oil and gas. These shocks had a direct impact on the investment performance and risk exposure of commodity-backed sovereign wealth funds. Many were forced to reevaluate their asset allocations and liquidity buffers, especially those heavily invested in Western financial systems.

The freezing of Russian state assets by Western governments further raised alarms among countries such as China, Saudi Arabia, and other Gulf monarchies. As these nations began to question the safety of their reserves in the event of future geopolitical tensions or sanctions. As a result, some SWFs have started to diversify more actively away from Western-dominated markets and reassess their foreign policy alignments to mitigate this form of geopolitical risk.

This evolving landscape stressed the need for SWFs to strengthen their performance attribution models by incorporating other non-financial risk factors. As traditional tools often fail to account for external shocks like diplomatic tensions or sanctions. In response, there has been a renewed emphasis on transparent performance measurement, accountability, and risk-aware benchmarking, which are core elements reflected in GAPP 23 of the Santiago Principles. (Boubakri et al., 2023)

3. METHODOLOGY AND DATA

3.1 Data

This thesis uses several datasets related to the GPFG, with a particular focus on its portfolio holdings and self-reported benchmarks for its two primary asset classes: equities and fixed income. In addition, the dataset includes the returns of selected risk factors that will be used later in the performance attribution analysis.

The term GPFG refers to the Government Pension Fund Global, while NBIM denotes Norges Bank Investment Management, the entity officially responsible for managing the fund's assets.

The main dataset includes the monthly returns of the GPFG from January 1998 through December 2024, resulting in 324 monthly observations over 27 years. These returns are broken down by asset class, with separate series for equities and fixed income. The dataset also includes the returns of the self-defined benchmark, enabling direct computation of the tracking error and other performance measurements between the portfolio and its benchmark.

While the GPFG invests across a diversified portfolio that also includes unlisted real estate and, more recently, unlisted renewable infrastructure, these asset classes are excluded from the scope of this thesis. There are two primary reasons for this decision. First, the historical return data for real estate and infrastructure are neither as extensive nor as consistently reported as those for equities and fixed income. The GPFG began its real estate investments in 2011, while renewable infrastructure was added as a separate allocation only in late 2020 (NBIM, 2024). In contrast, equity and fixed income returns have been reported consistently since 1998, providing a robust and continuous dataset suitable for long-term performance attribution analysis. Second, these alternative assets still represent a relatively small share of the fund's total portfolio. Moreover, as of 2024, unlisted real estate and infrastructure together only accounted for less than 5% of the fund’s overall assets under management (NBIM, 2024). For this research, which prioritizes data continuity and representativeness, the analysis will therefore focus exclusively on the GPFG’s equity and fixed income asset classes.

For consistency, all return data are converted and analyzed in U.S. dollars (USD), rather than Norwegian kroner (NOK) or euros (EUR). This decision reflects the currency denomination of most of the style factor return series, particularly those sourced from the Kenneth R. French Data Library and Roberco and ensures uniformity in the performance evaluation across all components.

The GPFG's return data and corresponding benchmark figures are publicly available on the NBIM website under the “Reports and Data” section. The factor return series used in this study, such as market, value, and size premiums, are mostly obtained from the Kenneth R. French Library for the equity segment, and Roberco for the Fixed Income segment, which provides standardized datasets widely used in empirical finance research.

The second dataset used in this thesis consists of the returns of the GPFG’s self-reported benchmark. Unlike standard market benchmarks, these benchmarks are internally constructed by the fund to align more closely with its strategic asset allocation. While they serve the same purpose, measuring performance relative to a defined reference portfolio, the GPFG’s benchmarks differ in that their exact composition is not publicly disclosed, especially in terms of individual holdings. However, their construction and methodology are clearly outlined in official documentation.

The benchmark returns, similar to the GPFG’s returns, are available from January 1998 to December 2024, yielding 324 monthly observations. This ensures a continuous data series without the need for constant interpolation or estimation. The benchmark portfolio represents the Ministry of Finance's neutral investment strategy. For the equity compartment, it is constructed using indices provided by FTSE Group and Bloomberg. The fixed income benchmark, on the other hand, is based on Bloomberg Barclays Indices.

As of December 2024, the cut-off date for this analysis, the benchmark allocation stood at 72.28% in equities and 27.72% in fixed income, consistent with the fund's long-term target allocation of approximately 70% equity and 30% fixed income. It is important to note that this allocation reflects only the equity and fixed income components of the portfolio, excluding other asset classes such as real estate and infrastructure, which are managed separately and not included in the benchmark allocation figures.

The benchmark presents a strong geographical concentration. The equity portion is heavily weighted towards North America, particularly the United States, which accounts for 57.10% of the holdings. Similarly, the fixed income portfolio is dominated by securities quoted in U.S. dollars, which make up 52.98% of the portfolio's currency exposure. To ensure sufficient exposure to European markets, the equity benchmark uses a regional weighting system based on the FTSE Global All Cap Index, with adjustment factors as follows: 2.5 for European developed markets (excluding Norway), 1.0 for the U.S. and Canada, 1.5 for other developed markets, and 1.5 for emerging markets. The fixed income allocation consists of 70% developed market government debt and 30% developed market corporate bonds (NBIM, 2024).

The third dataset consists of the return series for five major equity style factors: all sourced from the Kenneth R. French Data Library. These factor returns are denominated in U.S. dollars to ensure consistency with the GPFG's equity and fixed income data. The period for this dataset also covers the period from January 1998 to December 2024, aligning with the rest of the analysis.

This study uses the Fama and French Three-Factor Model, the extended Five-Factor Model, and the Three-Factor Model for developed markets. These models are widely adopted in empirical finance for their explanatory power regarding cross-sectional variations in stock returns. They incorporate key risk factors such as market excess return, size (SMB), value (HML), profitability (RMW), and investment (CMA). To enhance analytical precision and isolate the contribution of each factor, the study will also include individual regressions for every component. Additionally, the Carhart Momentum Factor (UMD) is incorporated to capture return persistence effects that are not addressed by the original Fama and French frameworks. Momentum, a well-documented market anomaly, reflects the tendency of past winners to outperform in the short term and adds further depth to the performance attribution analysis.

Regarding fixed income, this thesis uses datasets provided by Robeco, which publishes historical return series for factor investing in corporate bonds. Two main fixed-income indices are selected for analysis: the LUACER Index and the LF98ER Index. The LUACER Index tracks the performance of U.S. dollar-denominated investment-grade corporate bonds rated BBB- or higher by Standard & Poor's, representing securities with relatively low credit risk. In contrast, the LF98ER Index represents U.S. dollar-denominated high-yield (or "junk") corporate bonds rated below BBB, thus reflecting higher credit risk and return volatility. Including both indices allows for a comparison between low-risk and high-risk segments of the corporate bond market within the GPFG's fixed income allocation. In this thesis, the LUACER Index will be referred to as IGCORP for simplicity, whereas the LF98ER Index will be referred to as HYCORP.

All returns are denominated in U.S. dollars to maintain consistency with the factor datasets and to eliminate foreign exchange fluctuations. For the Brinson-Hood-Beebower (BHB) attribution model, annual aggregate returns will be calculated using geometric compounding, and portfolio weights will be averaged geometrically to accurately reflect the compounding nature of long-term investment returns. In contrast, for the factor-based performance attribution models, arithmetic returns will be employed. This is standard practice in regression-based frameworks, where arithmetic returns facilitate linear modeling and allow for clearer interpretation of factor exposures and contributions.

For the measurement of volatility, a logarithmic approach will be applied to estimate average annual volatility. The use of geometric returns is particularly appropriate in this context, as it more accurately captures the compounding effect of returns over time, an essential consideration for evaluating investment performance across multiple periods. The computed periods for this study are based on calendar years. The total geometric return over a given period is defined by:

$$(1 + R_{total}) = \prod_{t=1}^{T}(1 + R_t)$$

The compounding effect in geometric returns arises from the multiplicative structure of periodic returns.

When computing average returns, portfolio weights, or volatility measures, the geometric average is used to remain consistent with the compounding process. The geometric average return is defined as:

$$G = \left(\prod_{i=1}^{n}(1 + R_i)\right)^{\frac{1}{n}} - 1$$

Where:

- R_i represents the return in period *i*,
- *n* is the number of periods.

Since the data are reported monthly, and annual metrics are being calculated, this typically results in 12 periods per year. However, in practice, when computing the total annual geometric return, the exponent simplifies to 1 (i.e., $\frac{12}{12}$), so the division by the number of periods is not needed. This ensures that annualized figures reflect actual investment performance over the calendar year without distorting the compounding nature of returns.

A logarithmic approach is used for volatility computation because realized volatility is always positive and has a typical long-term average, like the S&P 500's average of about 16% per year. Volatility data also often includes some very high extreme values that can misrepresent the analysis. Taking the natural log helps by spreading out the values near the average, where most data points lie, and pulling in the very large extreme values. This makes the data easier to work with and more balanced for analysis.

3.2 Methodology

3.2.1 Research design and objectives

The main objective of this study is to evaluate the effectiveness of performance attribution methods for sovereign wealth funds by taking the GPFG as a case study, during periods of geopolitical stress. This will be achieved by applying two complementary frameworks: an enhanced version of the Brinson, Hood, and Beebower (BHB) model, and a factor-based attribution model that draws on the same BHB allocation components but incorporates statistical factor analysis. The analysis focuses on the GPFG of Norway, using monthly data from January 1998 to December 2024. This 27-year timeframe is broad enough to include major episodes of geopolitical and economic disruption, such as the 2008 global financial crisis, the COVID-19 pandemic, and the war in Ukraine beginning in 2022.

3.2.2 Data Collection and Preparation

The first stage of the research involves consolidating all relevant datasets, including GPFG returns, benchmark indices, and factor returns, into a single, structured Excel file. This preparation step ensures consistency across data sources and facilitates the application of more advanced formulas and models during the analysis phase.

3.2.3 Dual-Model Attribution Framework

The dual-method structure of this research allows for a detailed examination of return attribution. The BHB model provides insights into the impact of strategic asset allocation and selection decisions. While the factor-based approach enables a decomposition of returns into underlying sources of systematic risk, it also allows for a breakdown of allocation effects into exposures driven by factor allocation versus those attributable to idiosyncratic or unexplained components. By structuring the factor model around core components such as market, size, value, and momentum factors, this statistical method provides a complementary perspective to the allocation-driven framework of the BHB model. And together, they offer a comprehensive view of the GPFG's performance dynamics during volatile market environments. (Brinson, Hood, & Beebower, 1986; François and Hübner, 2024)

3.2.4 Overview of the Multifactor Attribution Model

The multifactor model applied in this study is based on the framework developed by Fama and French (1993). Unlike the traditional Capital Asset Pricing Model (CAPM), which explains asset returns using a single beta representing sensitivity to market movements, the multifactor approach incorporates additional risk factors such as size, value, or momentum. This extended framework is widely adopted in performance attribution, as it enables a more detailed decomposition of returns into their underlying drivers. In this analysis, the multifactor model will be used in the return-based style analysis to differentiate between returns generated through active management and those attributable to systematic exposure to common risk factors, while also accounting for the actual portfolio holdings.

With the assembled dataset and a structured methodology, this study aims to conduct a comprehensive performance attribution analysis. As noted by Braga, M.D. (2024), the objective of performance attribution is to break down the total return into its underlying decision components, assign a value or percentage to each, and evaluate the impact of individual factors on overall performance.

The first step in the analysis involves a detailed decomposition of the GPFG's performance. Following François and Hübner (2024), this granular breakdown enables the identification of the primary contributors to return. The analysis will begin by assessing the contribution of each asset class, guided by the three foundational principles of performance attribution outlined by Spaulding (2003):

1. The sum of the contribution effects should always equal the portfolio's total return at any given point in time.

This relationship can be expressed as:

$$R_{\{P,t\}} = \sum_{\{i=1\}_i^{\{N\}c} R_{\{i,t\}}} c_i R_i, t$$

2. The weight of each asset at time t should be measured in a way that excludes any market effect occurring during the time interval. This ensures that the attribution reflects actual allocation decisions rather than market-driven price changes.
3. The cash position, if present, must be treated as one of the assets within the portfolio. It should be included in the total number of assets *N* when calculating contributions and weights. However, for this thesis, cash will not be included as an asset class since it is not reported by NBIM.

3.2.5 Decomposing the Sharpe ratio

To deepen the analysis, the Sharpe ratio decomposition analysis, as developed by Steiner (2011), will be used. The process begins with the standard Sharpe ratio, which measures the ratio of portfolio excess return to portfolio volatility. The return series obtained from the NBIM website is already net of the risk-free rate, which is based on the 1-month U.S. Treasury bill rate sourced from the Kenneth R. French Data Library. This risk-free rate is particularly suitable because it matches the periodicity and calculation method of the factor data used in this analysis, simplifying the process.

Additionally, using the 1-month T-bill rate as a proxy, with slightly shorter maturity than the more common 3-month rate, provides a more precise proxy for the monthly returns reported by NBIM. Since the factor analysis's market risk premium (RM-RF) also uses this same risk-free rate, applying it consistently across this study ensures coherence in the RBSA regression without requiring adjustments or conversions of the rates.

The Sharpe ratio formula is as follows:

$$S_p = \left(R_p - R_f\right)/\sigma_p$$

Where:

- Sp is the standard Sharpe ratio
- Rp is the expected return
- Rf is the risk-free rate
- σp is the Standard Deviation.

The second step involves decomposing the Sharpe ratio by calculating each asset class's contribution. This is done by weighting the asset's impact and multiplying both the numerator and denominator by the terms ρi and σi, where ρi represents the correlation between the assets or compartment's return and the total portfolio return, and σi is the yearly geometric average volatility of that asset class. As noted earlier in this thesis, the absence of security-level allocation data necessitates analyzing contributions at the compartment level, with each compartment treated as a single asset class to estimate its aggregate impact on the portfolio's risk-adjusted performance.

$$S_p = \sum_{i=1} n \left(w_i \cdot \rho_i, p \cdot \sigma_i/\sigma_p \cdot 1/\rho_i, p \cdot r_i/\sigma_i\right)$$

Where:

- $w_i \cdot \rho_i, p \cdot \sigma_i/\sigma_p$ is the risk weight and refers to the contribution of an individual asset (or factor) to the total risk of a portfolio, which is here measured by the standard deviation. It helps investors understand how much each component influences the overall portfolio risk.
- $1/\rho_i, p \cdot r_i/\sigma_i$ It is the Component Sharpe Ratio, and it measures the risk-adjusted contribution of each asset class to the overall portfolio's Sharpe Ratio. It helps identify which components improve or hurt the portfolio's performance relative to risk.

This decomposition goes beyond a general explanation of risk-adjusted return by showing how each compartment contributes to the portfolio's overall risk-adjusted performance.

While Steiner (2011) primarily discusses individual assets, the approach can be adapted to focus on broader investment compartments, such as Fixed Income and Equity, by substituting these compartments in place of individual assets.

The first part of the decomposition is referred to as the Risk Weight, which quantifies how much risk each compartment contributes to the total portfolio. It is calculated by adjusting the compartment's portfolio weight to reflect its risk contribution. Including this measure is important because even compartments with small weights can negatively impact returns if they contribute disproportionately high risk.

The second part of the equation is the Component Sharpe Ratio, which measures the contribution of each compartment to the portfolio's total risk-adjusted return.

3.2.6 Fama's Performance Decomposition Framework (1972)

To deepen the understanding of return attribution, the analysis begins with the performance decomposition framework outlined by Fama (1972), which identifies the components that must be combined to arrive at the final portfolio return of the GPFG.

$$R_a - R_f = \left(R_a - R_x(\beta_a)\right) + \left(R_x(\beta_a) - R_f\right)$$

Where:

- *Ra–Rf* is the Overall performance, with Ra being the return of the GPFG, and *Rf* the risk-free rate
- $\left(R_a - R_x(\beta_a)\right)$ is the Selectivity. R_a is the return of the GPFG, while $R_x(\beta_a)$ is the expected return
- $\left(R_x(\beta_a) - R_f\right)$ is the risk part of the total performance

The following formulas will facilitate a performance attribution at multiple levels: policy, strategic, tactical, and selection.

3.2.7 The Brinson, Hood, and Beebower Attribution Model (BHB)

3.2.7.1 General Context

The Brinson-Hood-Beebower (BHB) model, introduced in the original 1986 paper "Determinants of Portfolio Performance" by Gary P. Brinson, L. Randolph Hood, and Gilbert L. Beebower, is a foundational framework in the field of investment management for attributing portfolio performance (Brinson, Hood, & Beebower, 1986). Developed to provide pension plan sponsors and investment managers with a clear method to evaluate the contributions of various investment decisions, the BHB model decomposes portfolio returns into three primary components: investment policy (asset allocation), market timing, and security selection. This approach has become a standard tool in performance attribution, widely adopted in both academic research and industry practice.

The BHB model emerged during a period when institutional investors, particularly pension funds, required better clarity in assessing the effectiveness of their investment strategies. Before its development, performance evaluation often lacked a regular framework to distinguish between the effects of long-term asset allocation decisions and active management choices. The BHB model addressed this gap by introducing a methodology that compares the actual portfolio returns against a passive benchmark portfolio, which reflects the long-term asset allocation policy weighted by the benchmark returns of each asset class, which is precisely the case in this study with GPFG, where the fund's actual returns will be compared against its self-reported passive benchmark

Through an empirical analysis of 91 large U.S. pension plans over the period from 1974 to 1983, Brinson et al. (1986) demonstrated that investment policy (i.e., the strategic asset allocation) explained, on average, 93.6% of the variation in total portfolio returns, underscoring its dominant role over market timing and security selection.

The significance of the BHB model lies especially in its simplicity and practical applicability. By quantifying the impact of asset allocation versus active management, the model provided a rigorous framework for investors to evaluate whether outperformance (or underperformance) was due to strategic decisions or tactical choices. This insight shifted the focus of institutional investment management toward optimizing asset allocation, while also highlighting the challenges of consistently achieving excess returns through market timing or stock picking. The model's influence extends beyond theory, as it has shaped the design of modern portfolio management practices, including the rise of passive investing and index funds.

Other methodologies for performance attribution also existed before the BHB model, notably the Brinson-Fachler model (1985), which refined the allocation effect calculation by accounting for sector performance relative to the overall benchmark. This model introduced methodological advancements that allowed for a more detailed decomposition of portfolio performance. While both models remain relevant, the BHB model is particularly noted for its application in equity return attribution.

3.2.7.2 The standard Brinson, Hood, and Beebower Attribution Model (BHB)

The main focus for this thesis will be the BHB performance attribution model, which builds on Fama's performance decomposition framework. This model aims to explain the drivers of excess return by dividing performance into four key components: allocation (also referred to as timing in the BHB model), selection, and interaction effects.

- Allocation refers to the decision to overweight or underweight certain asset classes.
- Selection captures the impact of choosing securities that outperform or underperform within those asset classes.
- Interaction measures the combined effect that occurs when allocation and selection decisions influence each other simultaneously.

The BHB model uses these four components, often represented in a quadrant table, to provide a structured analysis of portfolio returns.

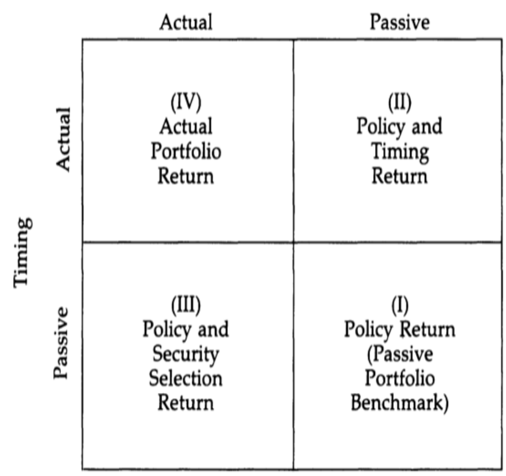

Figure 3: Performance Attribution Framework — Brinson, Hood, and Beebower (1986)

The first quadrant represents the policy return, corresponding to the benchmark return based on the strategic asset allocation. The second quadrant, often referred to as the timing return, captures the effects of market timing through dynamic adjustments in asset weights relative to the benchmark. The third quadrant measures the return attributed to security selection, reflecting the stock-picking decisions made within each asset class while keeping the overall strategic allocation. Finally, the fourth quadrant represents the total portfolio return, which combines the effects of policy allocation, timing, and security selection, thus reflecting the realized return from all investment decisions.

These components are formally defined by the four equations presented below, along with an additional equation that accounts for their interaction effects.

It is worth noting that in the context of this analysis, it will be standard practice to replace individual assets with broader investment compartments when applying these performance attribution formulas.

- Timing: II - I
- Selection: III - I
- Other: IV- III - II + I
- Total: IV – I

Each compartment in the Brinson, Hood, and Beebower (BHB) model represents a distinct source of portfolio return, allowing for the decomposition of the total return into significant components. These compartments help analyze how different investment decisions contribute to overall performance.

The analysis begins with the allocation, which captures the effect of overweighting or underweighting asset classes relative to the benchmark. Allocation shows the impact of different portfolio weights from the benchmark weights while assuming benchmark returns for each asset class.

$$Allocation = \sum\left[\left(W_a i \times R_p i\right) - \left(W_p i \times R_p i\right)\right]$$

Where:

- $W_a i$ is the weight of the compartment I in the GPFG
- $R_p i$ is the return of the benchmark for the compartment *i*
- $W_p i$ is the return of the compartment in the benchmark

Next, the focus shifts to the selection effect, which captures the impact of selecting securities within each asset class that outperform or underperform the benchmark returns for that asset class. Selection reflects the value added (or lost) by active stock picking or security selection.

$$Selection = \sum\left[\left(W_p i \times R_a i\right) - \left(W_p i \times R_p i\right)\right]$$

Where:

- $R_a i$ is the return of the compartment I for the GPFG

Finally, the interaction term measures the combined effect of allocation and selection happening simultaneously. It captures the overlap when the portfolio deviates from the benchmark weights and the selected securities perform differently from the benchmark.

$$"Other"\ or\ Interraction = \sum\left[\left(W_a i - W_p i\right) \times \left(R_a i - R_p i\right)\right]$$

The total excess return of the portfolio relative to the benchmark is the sum of the three components: allocation, selection, and interaction. This total shows how much the portfolio's performance differs from the benchmark due to decisions about asset allocation, security selection, and their combined effects.

$$Total = \sum\left[\left(W_a i \times R_a i\right) - \left(W_p i \times R_p i\right)\right]$$

3.2.7.3 The geometric Brinson, Hood, and Beebower Attribution Model

The previous explanation serves as a groundwork for understanding how performance attribution is generally structured and how allocation, selection, and interaction effects are conceptually defined. By revisiting the original BHB framework and its limitations in the context of geometric return calculations, it becomes clear why a more refined approach is necessary.

It is important to note, however, that while the geometric model is used for analyzing the actual portfolio performance, the logic of the traditional BHB attribution model will still be applied later in this thesis, specifically, for the construction of a factor-based attribution model. In that context, BHB-style compartmental logic will be adapted to isolate the contribution of exposures to various systematic risk factors.

This leads to the actual model primarily used in this study, one that is specifically designed to work with geometrically compounded returns and time-consistent weighting. The methodology developed by Burnie, Knowles, and Teder (1998), and later improved by Weber (2018), provides a suitable alternative. This refined model introduces slightly different components: the geometric allocation, selection, and interaction effects. It allows for a top-down performance attribution framework that fully incorporates the geometric properties of return calculation. In doing so, it adapts and extends the original Brinson-Hood-Beebower and Brinson-Fachler frameworks to better reflect the compounding nature of long-term investment performance.

The main analysis in this thesis will therefore apply this geometric attribution model, beginning with the general formula that expresses the total excess return of the portfolio over the benchmark as the sum of three effects: geometric allocation, geometric selection, and geometric interaction. The starting point is:

$$Rp - Rb = \frac{\left(1 + R_p\right)}{\left(1 + R_B\right)} - 1 = [(1 + A^g) \times (1 + S^g) \times (1 + I^g)] - 1$$

Here, A^g, S^g, and I^g represent the geometric Allocation, Selection, and Interaction effects, respectively, for the entire portfolio.

The allocation effect is given as:

$$Allocation\ =\ (1\ +\ R\_\{B(N)\})/(1\ +\ R\_B)\ -\ 1$$

Where:

- $R_{B(N)} = \Sigma\left(w_p, i \times R_B, i\right)$ is the notional allocation portfolio return

The selection Effect is given as:

$$Selection^{g} = \left(1 + R_{B(S)}\right) / \left(1 + R_{B(N)}\right) - 1$$

Where:

- $\mathrm{R\_\{B(S)\}} = \Sigma\,(\mathrm{w\_B, i} \times \mathrm{R\_p, i})$ is the return of the notional selection portfolio

As for the BHB model, the interaction model is the cross product of the allocation and selection effects.

$$Interraction^{g} = \left[\left(1 + R_{p}\right) / \left(1 + R_{B(S)}\right)\right] \times \left[\left(1 + R_{B(N)}\right) / \left(1 + R_{B}\right)\right] - 1$$

A key specificity of the geometric attribution model is the introduction of two intermediary concepts: the Notional Allocation Portfolio and the Notional Selection Portfolio. These are not actual portfolios, but rather conceptual tools used to isolate and quantify the individual effects of allocation and selection under a geometric framework.

The Notional Allocation Portfolio is constructed by applying the portfolio's actual weights to the benchmark returns. It represents the return that would have been achieved if the manager had only made allocation decisions, choosing how much to invest in each compartment, without deviating from the benchmark's performance within those compartments. It captures the impact of over- or underweighting asset classes relative to the benchmark.

The Notional Selection Portfolio, on the other hand, applies the benchmark weights to the portfolio's actual returns. It reflects what the return would have been if the manager had made no allocation decisions but had instead generated active returns through security selection within each asset class.

These two intermediate portfolios are essential in decomposing the total geometric excess return into allocation, selection, and interaction effects. By comparing these notional returns with the actual and benchmark returns, the model effectively isolates the contribution of each decision-making process while accounting for the compounding nature of returns.

The notional allocation Portfolio is represented as:

$$NA = \left(\sum (w_{\mathrm{pi}} \times R_{b\mathrm{i}})\right)$$

The notional selection portfolio is represented as:

$$NS = \sum (w_{b\mathrm{i}} \times R_{\mathrm{pi}})$$

To validate the computed geometric allocation, selection, and interaction effects, this study applies the Burnie, Knowles, and Teder (BKT) equation. This equation confirms that the geometric excess return of the portfolio over the benchmark should equal the compounded impact of these three effects. The relationship is expressed as follows:

$$r^{g}_{P-B,t} = \left(1 + \mathcal{A}^{g}_{\mathcal{P},t}\right)\left(1 + \mathcal{S}^{g}_{\mathcal{P},t}\right)\left(1 + J^{g}_{P,t}\right) - 1$$

Where:

- $\mathcal{A}^{g}_{\mathcal{P},t}$ represents the net allocation Effect with the use of the notional Allocation Portfolio

- $\mathcal{S}^{g}_{\mathcal{P},t}$ represents the net selection effect with the use of the notional selection portfolio
- $J^{g}_{P,t}$represents the net interaction effect, combining both into one single effect on the portfolio performance
- $r^{g}_{P-B,t} \equiv \frac{1+R_{P,t}}{1+R_{B,t}} - 1$ is the geometric return differential between the portfolio and the benchmark

The equality between these two equations results from their common goal of measuring the portfolio *P*'s excess geometric return relative to its benchmark *B*, but simply from two complementary perspectives. The first equation $\left(1 + \mathcal{A}^{g}_{\mathcal{P},t}\right)\left(1 + \mathcal{S}^{g}_{\mathcal{P},t}\right)\left(1 + J^{g}_{P,t}\right) - 1$ decomposes the excess return into the combined effects of active management decisions, namely, the allocation effect, the selection effect, and the interaction effect. In contrast. Whereas $r^{g}_{P-B,t} \equiv \frac{1+R_{P,t}}{1+R_{B,t}} - 1$ directly measures the total geometric excess return of the portfolio over the benchmark. When the geometric allocation, selection, and interaction effects are fully decomposed, it becomes evident that these two formulations represent different facets of the same underlying return differential.

3.2.8 Factor-based Attribution model

3.2.8.1 General Context

The study of how investment funds allocate their capital has evolved significantly over time, beginning with initial strategies such as strategic and tactical asset allocation. These early approaches categorized investments into broad categories, typically equities, fixed income, and cash, and were rooted in the Modern Portfolio Theory (Markowitz, 1952). This framework introduced the principle of diversification as a tool to balance risk and return, using historical data to construct efficient portfolios. Later, Tactical Asset Allocation emerged as a more dynamic strategy, enabling investors to adjust their portfolio weights in the short term based on macroeconomic signals or market forecasts. This method gained popularity in volatile environments, where fixed allocation techniques were insufficient.

As financial research and data analytics advanced, more refined allocation strategies emerged, most notably factor-based allocation. This approach differs from traditional asset class distinctions, instead assigning weights based on systematic risk factors such as value, size, momentum, quality, or low volatility. Developed largely through the work of Fama and French (1992, 2015), this methodology aims to isolate the true drivers of portfolio performance by linking returns to specific, empirically supported factors rather than general asset classes.

In a key contribution to this area, Bessler, Taushanov, and Wolff (2021) compared sector-based and factor-based portfolio construction using an optimization framework. Their study evaluated how both strategies performed across different economic regimes, including both stable periods and crises such as the 2008 Global Financial Crisis and the COVID-19 pandemic. They found that factor-based portfolios generally delivered stronger long-term risk-adjusted returns, mainly due to exposure to rewarded factors like momentum and quality. However, sector-based portfolios tended to offer better downside protection during extreme market events; for instance, during the 2008 financial crisis, they experienced smaller drawdowns. These findings suggest that both allocation methods are worth considering, depending on the investor's priorities and prevailing market conditions.

Their conclusions further highlight the importance of economic and financial cycles in determining which strategy is more effective. During periods of economic expansion, factor portfolios tend to benefit more from market momentum and valuation trends. In contrast, during downturns, sector diversification can play a more defensive role. Bessler et al. (2021) thus advocate for a hybrid strategy that combines both sector and factor perspectives to enhance portfolio stability over time.

Angelidis and Tessaromatis (2017) extended the factor-based approach to the international level by examining whether country-level exposures to factors like value, momentum, and quality could enhance global equity allocations. Rather than focusing only on stocks or sectors, they constructed country portfolios guided by these factors. Their results showed consistent outperformance over traditional market-cap-weighted benchmarks, with better risk-adjusted returns and lower drawdowns. This added a geographic dimension to factor investing, suggesting that factors can guide not only asset class or sector choices but also global allocation decisions.

Altogether, the shift from traditional asset-based allocations to more specified, factor-driven approaches reflect a broader trend toward research-driven portfolio construction. These studies highlight the relevance of factor-based models in performance attribution, especially when evaluating return sources during periods of increased uncertainty. In this study, the factor-based attribution model will be used in parallel with the traditional BHB framework, which will be adapted in a later section to account for factor exposures, offering a more comprehensive view of the drivers behind sovereign fund performance during geopolitical stress. As explained by François and Hübner (2024), this model can be constructed using the same foundational principles as the BHB approach. It complements the beginning-of-period portfolio holdings with statistically estimated factor exposures, allowing for a more detailed decomposition of performance across systematic risk dimensions, and offering a more comprehensive view of the drivers behind sovereign fund performance during geopolitical stress.

3.2.8.2 Factor Choice

The Fama-French three-factor model, which includes market risk (Rm-Rf), size (SMB), and value (HML) factors, is widely used in finance literature to explain the variations in equity returns. These factors capture fundamental dimensions of risk and return associated with equity portfolios. Additionally, for the fixed income component of the GPFG, factors such as credit spreads, term premiums, and liquidity premiums are crucial for understanding the performance dynamics, as they address the unique risk characteristics of bonds and other debt instruments.

Performing regressions separately on the whole fund, the equity compartment, and the fixed income compartment allows for a detailed analysis of how returns are linked to relevant risk factors across asset classes. The whole fund regression offers a comprehensive view of the GPFG's performance drivers, while separate analyses enable more precise identification of factor exposures specific to equities or fixed income. This separation helps in better understanding how each segment's returns relate to underlying risk factors, which is essential for a correct and meaningful attribution of performance.

The inclusion of the Fama-French developed markets factors in the equity analysis is particularly important due to the GPFG's broad geographical diversification. According to Norges Bank Investment Management, the fund's equity investments span various sectors and regions, with the largest exposures in North America and Europe, followed by developed markets in the Asia-Pacific region and emerging markets (NBIM, 2024). Incorporating these developed markets factors captures region-specific risk premia and return patterns, aligning the model with the fund's actual international investment strategy. This comprehensive factor approach ensures a more accurate understanding of the drivers behind the GPFG's returns and facilitates a robust and economically relevant performance attribution.

While several methods exist for estimating style exposures, including the ridge regression approach proposed by LoBosco and DiBartolomeo (1992), this study might make use of Principal Component Analysis (PCA) not for performance attribution directly, but as a diagnostic tool to assess the dimensionality of the factor universe. As it enables an objective determination of how many factors to retain in the model by identifying the number of components that capture the majority of variance across style and risk premia. Once the number of factors is justified, a traditional OLS-based regression is used for returns-based style attribution.

3.2.8.3 Factor-Based Attribution Model

In this study, attributing the returns of the GPFG to specific management decisions represents a key component of the broader risk-based analysis. However, to complete the picture, it is essential to incorporate a factor-based attribution approach. This complementary analysis aims to identify the underlying investment styles to which the GPFG is exposed. By applying the same logic used in the Brinson, Hood, and Beebower (BHB) framework, a return-based style analysis can be conducted using relevant risk factors. This will allow for the identification of those factors that best explain the fund's return patterns and offer insights into the investment "style" implicitly followed by its management. As demonstrated by François and Hübner (2024), the portfolio's excess return can be expressed through a multifactor model, using the Brinson attribution model as a conceptual foundation.

$$R_{P,t} - R_{B,t} = \sum_{l=1}^{L} \left(\beta_{P,l,t} - \beta_{B,l,t}\right) \times F_{l,t} + \left(\beta_{P,0,t} - \beta_{B,0,t}\right)$$

Where:

$\beta_{P,l,t} = \sum_{i=1}^{N} w_{P,i,t} \times \beta_{i,l}$ is the sensitivity of the portfolio return to the lth statistical factors
$\beta_{P,0,t}$ is the weighted sum of each compartment's abnormal return and the noise term.

A closer examination of this equation leads to a similar conclusion to that of François and Hübner (2024), who note that the first component essentially mirrors the allocation effect as defined in traditional performance attribution. By analogy, the remaining term can then be interpreted as capturing the combined effects of selection and interaction.

Accordingly, the equation is reformulated as follows:

$$R_{P,t} - R_{B,t} = \sum_{l=1}^{L} \left(\beta_{P,l,t} - \beta_{B,l,t}\right) \times F_{l,t} + \sum_{k=1}^{K} w_{P,k,t}\, \delta_{P,k,t} - \sum_{k=1}^{K} w_{B,k,t}\, \delta_{B,k,t}$$

Where:

- $\delta_{P,k,t}$ & $\delta_{B,k,t}$ are respectively the idiosyncratic returns of the portfolio and the benchmark for each segment.

Merging both equations allows us to directly find the equations of the three separate effects as seen below:

$The\ Allocation\ Effect$:

$$\mathcal{A}_P, t = \sum_{l=1}^{L} (\beta_P, l, t - \beta_B, l, t) \times F_l, t + \sum_{k=1}^{K} (w_P, k, t - w_B, k, t) \times (\delta_B, k, t - \delta_B, t)$$

Where:

- δ_B, k, t is the benchmark's idiosyncratic risk for the compartment k

$The\ Selection\ Effect$:

$$\mathcal{S}_P, t = \sum_{k=1}^{K} w_B\,, k, t \times (\delta_P, k, t - \delta_B, k, t)$$

$The\ Interraction\ Effect$:

$$\mathcal{I}_P, t = \sum_{k=1}^{K} (w_P, k, t - w_B, k, t) \times (\delta_P, k, t - \delta_B, k, t)$$

Where:

- $\delta_B, t = \sum_{k=1}^{K} w_B\,, k, t \times \delta_B, k, t$: and it represents the benchmark's idiosyncratic risk, capturing the proportion of the benchmark return that cannot be explained by exposure to systematic risk factors and instead comes from the unique characteristics of the benchmark's components

- $\sum_{l=1}^{L} (\beta_P, l, t - \beta_B, l, t) \times F_l, t$ is the Factor effect, and it reflects the difference in factor exposures between the portfolio and its benchmark. It shows whether the portfolio manager has taken active positions by overweighting or underweighting certain risk factors relative to the benchmark, as well as shows how these factors contributed to the excess return

To ensure that the factor model applied in this study accurately reflects the investment philosophy of the GPFG, a structured approach is followed to select the factors that will be included in the analysis.

For the equity segment, the starting point is the Fama-French Five-Factor model (2015), which extends the classic three-factor model by including profitability (RMW) and investment (CMA) factors alongside the traditional market, size (SMB), and value (HML) factors. This model has gained widespread acceptance in empirical asset pricing, providing a comprehensive framework to explain the primary drivers of equity returns. The choice of these five factors is supported both theoretically and empirically, and they are frequently cited in studies related to institutional investors, including sovereign wealth funds.

Regarding the fixed income compartment, this thesis relies on datasets provided by Robeco, which offer historical return series relevant for factor investing in corporate bonds. Two key fixed-income indices are selected for analysis: the LUACER Index and the LF98ER Index. The LUACER Index represents U.S. dollar-denominated investment-grade corporate bonds rated BBB- or higher by Standard & Poor's, capturing securities with relatively low credit risk and moderate return volatility. This index serves as a proxy for duration and credit risk exposure within the investment-grade segment of GPFG's fixed income portfolio. Similarly, the LF98ER Index tracks U.S. dollar-denominated high-yield corporate bonds rated below BBB, reflecting higher credit risk and return volatility characteristic of lower-rated issuers.

By including both indices, this study captures the wide range of credit risk within the corporate bond market, allowing for a more refined analysis of GPFG's fixed income allocation across different credit ratings. These factor proxies align with NBIM's reported exposures to duration and credit risk, supporting their inclusion in the factor model for fixed income.

Their annual reports help confirm that many theoretically chosen factors align closely with the actual exposures managed by NBIM. For example, GPFG's documented exposures to value, size, quality, and momentum align with the equity factors selected here. Also, NBIM's identification of duration and credit risk exposure in the bond portfolio supports the inclusion of these fixed income factors. However, rather than relying solely on NBIM's 2023 study, this study independently estimates GPFG's factor exposures using return-based style analysis applied over rolling windows, each spanning one quarter, as per the initial reporting period of NBIM.

To maintain model robustness and avoid overfitting, factors are only retained if they satisfy several conditions: theoretical or institutional relevance, availability of clean and consistent data, statistical significance in regression tests, and low multicollinearity. This process ensures the final model is both statistically sound and reflective of the actual portfolio structure.

The first analytical step involves performing an unconstrained regression to identify the factors most relevant to GPFG's returns. This approach allows factors to exhibit any coefficient sign and does not restrict weights to sum to one, enabling a clear view of individual and combined explanatory power. By examining p-values and adjusted R^2 values, irrelevant or noisy factors can be excluded, retaining only those with strong explanatory power.

Following factor identification, a return-based style analysis, originally proposed by Sharpe (1992), is applied. This technique estimates the portfolio's exposure to multiple factor indexes simultaneously by regressing the portfolio returns against the returns of predefined factor portfolios. Unlike ordinary regressions, RBSA imposes constraints on factor weights, requiring them to be non-negative and sum to 1, which reflects realistic portfolio allocation limits. Sharpe's RBSA equation used in this study is as follows:

$$R_{i,t} = \alpha_i^{MF} + \sum_{k=1}^{K} w_{i,k} I_{k,t} + \epsilon_{i,t}$$

Sharpe (1992) introduced three forms of Return-Based Style Analysis, based on different constraint regimes, which helped later studies draw parallels to the efficient market hypothesis. The weak form allows no constraints on portfolio weights, allowing both positive and negative values to be present. The semi-strong form restricts some weights from being negative to avoid short selling, commonly applied to asset classes such as real estate. Lastly, the strong form excludes any negative weights altogether. For this study, we adopt the strong form, in line with Norges Bank Investment Management's Principles for Risk Management, which specify that short selling is only permitted under established borrowing arrangements subject to special monitoring. Since we do not have access to such arrangements, we assume no short selling and zero leverage.

To estimate the RBSA weights, François and Hübner (2024) recommend using quadratic optimization techniques to minimize the sum of squared errors. Accordingly, the error term will be reduced to its minimum for each quarter using a rolling window approach with the help of the Excel solver function. The weights will be updated dynamically for each reporting period, initially quarterly for the first 14 years, then semiannually as per data from NBIM reports since 2020. The initial weights are estimated from a regression on the first three months of returns, providing a standard for adjusting subsequent weights as new data accumulates. The Solver tool will be applied in each period to minimize errors while respecting the constraints, ensuring the estimated weights are optimal and consistent with the GPFG's observed returns.

While RBSA is conceptually straightforward, a Kalman filter approach, like the one employed by Mamaysky, Spiegel, and Zhang (2008) in mutual fund literature, would arguably be more suitable. The Kalman filter offers a single dynamic estimation procedure that updates directly each quarter using quadratic programming, eliminating the need for repeated regressions. This would be an excellent future research avenue. However, due to current limitations in mastering these advanced methods, this study relies on the RBSA approach described above.

Regarding factor selection, it is supported by theoretical considerations. NBIM does not directly classify its equity investment strategies as strictly passive or active. Instead, the fund uses a combination of strategies that include both efficient market exposure and fundamental research. While the majority of the equity portfolio is managed internally through efficient market exposure strategies, none of the investment strategies are 100% passive. NBIM invests broadly in the companies within the benchmark but seeks to avoid mechanical benchmark replication due to its associated high trading costs. Given the fund's size and global reach, it is essential to manage market exposure and trade efficiently. Additionally, NBIM emphasizes in-depth knowledge of its largest equity investments to achieve the highest possible return after costs, thereby improving risk management and fulfilling its ownership role. This approach reflects a sophisticated strategy that balances passive and active elements to optimize returns.

The GPFG's investments are broadly diversified and benchmarked against global indices, justifying the inclusion of the market risk premium (Rm–Rf) as a primary explanatory factor. The fund's exposure to smaller companies, including pre-IPO placements, supports the inclusion of the size factor (SMB). NBIM's focus on fundamental analysis and sector tilts further validates the use of the value factor (HML). Moreover, references to rotation and tilting strategies in the NBIM Strategy 25 report suggest that momentum can also play a relevant role (NBIM, 2022).

In the fixed-income segment, NBIM invests in a broad range of bonds from government and corporate issuers. The strategies aim to build cost-effective portfolios with exposure to key risk drivers, while also seizing opportunities at the security, issuer, and sector levels. This approach is custom-made to the specific characteristics of the fixed-income market, allowing the fund to manage risks effectively and capitalize on investment opportunities.

NBIM invests in both investment-grade and high-yield credit instruments, with documented allocations to corporate bonds rated below BBB–. This supports the inclusion of IGCorp and HYCorp factors as relevant credit risk exposures (NBIM, 2023). The fund's broad duration exposure implies sensitivity to the term premium.

Additionally, the fund's allocation to less liquid and long-duration positions introduces exposure to the liquidity risk premium. Finally, NBIM's growing emphasis on climate risk and ESG alignment, including its commitment to achieving net-zero emissions by 2050, justifies the inclusion of a possible climate or ESG factor in extended model specifications (NBIM, 2022)

This complex yet understandable investment policy suggests that while market exposure is a primary source of returns, there is also a deliberate element of active management aiming to capture factor exposures beyond simple benchmark replication. To reflect this, this study will use the Fama-French Five-Factor model to test the sources of returns and better capture the fund's factor exposures.

To evaluate whether the GPFG's exposure to systematic risk factors changes during periods of market stress, this study uses a dummy variable approach to test for time-varying factor sensitivities (betas). A dummy variable serves as a binary indicator, taking the value of 1 during specified crisis periods and 0 otherwise, to capture structural shifts in the relationship between returns and explanatory variables. In this analysis, the dummy identifies the same three distinct periods of financial market turmoil seen earlier: the 2008–2009 Global Financial Crisis, the first half of 2020 (COVID-19 pandemic), and the year 2022 marked by the Russia–Ukraine conflict, a surge in inflation, and aggressive monetary tightening policies.

The model introduces interaction terms between this crisis dummy and key risk factors included in the Returns-Based Style Analysis, specifically the factors that are chosen after the final screening. These interaction terms allow the estimation of changes in the GPFG's exposures during crisis periods relative to normal market conditions. This analysis is particularly relevant given the fund's long-term investment horizon and its stated objective of maintaining stable risk exposures over time. Testing whether these exposures shift in turbulent markets also allows for an assessment of the robustness of the GPFG's strategic allocation under stress.

4. RESULTS

This section presents the results of the performance analysis of the GPFG over the period 1998–2024. It includes an overview of descriptive statistics and factor selection for the RBSA, as well as the calculation of geometric annual returns for both the GPFG and its benchmark. Furthermore, the BHB geometric attribution method is used to decompose the GPFG's excess returns into allocation, selection, and interaction effects. Together, these results should offer valuable insights into the fund's primary performance drivers and establish a foundation for the subsequent analysis of factor exposures and performance under geopolitical stress periods.

4.1 Descriptive Statistics

The performance of the Government Pension Fund Global over the period from 1998 to 2024 reveals a strong long-term return profile. The fund achieved an average annual geometric return of 7.38%, with the highest annual return recorded in 2009 at approximately 30.05%. Equity investments within the fund delivered an average geometric return of 9.19%, while fixed income assets yielded a more modest average of 4.07%. The benchmark displayed similar patterns, with an average annual geometric return of 7.06%. Its peak performance also took place in 2009, with a total return of approximately 25.65%. Within the benchmark, the equity component averaged 8.71% annually, and the fixed income component averaged 3.78%.

Over the observed period, the GPFG exhibited an average annual tracking error of 1.12%. At first glance, this may appear relatively high for a fund that is often described as adhering to a passive investment strategy. However, as discussed in the methodology section, the GPFG does not follow a simple replication approach. Instead, while it aims to stay close to its benchmark, it uses active strategies within the defined risk limits, including strategies related to factor changes, environmental and ethical exclusions, and opportunistic allocations. Moreover, the use of geometrically compounded returns in performance reporting contributes to the high tracking error figure. When tracking error is computed using compounded annual returns, it captures not only the monthly deviations between the fund and the benchmark but also the cumulative effect of those deviations over time. As a result, even small month-to-month differences can accumulate and inflate the annual tracking error. To test this hypothesis, tracking error is also calculated using monthly return data without geometric aggregation. In that case, the tracking error is notably lower, at 0.63%, providing a more accurate reflection of how closely the fund tracks its benchmark in practice.

Regarding risk, the overall standard deviation of the GPFG is calculated at 2.75%. The equity component exhibits an average standard deviation of 4.1%, whereas the fixed income component displays a lower volatility of 1.8%. For the benchmark, the corresponding figures are slightly higher in total, with an average standard deviation of 2.83%, 4.1% for equities, and 1.9% for fixed income instruments.

Asset allocation within the GPFG evolved significantly over the period in response to changing economic conditions and policy decisions made by the Norwegian government. In 1998, the portfolio was initially composed of approximately 70% fixed income securities and 30% equities. Over time, this composition shifted drastically, reaching a target allocation of roughly 70% equities and 30% fixed income. On average across the entire period, equities constituted around 55% of the portfolio, while fixed income accounted for 45%. It is important to note that the equity-heavy composition prevailed for a considerably longer portion of the period under study.

The fund also shows strong risk-adjusted performance. The average Sharpe ratio for the GPFG total portfolio is 2.68, with the equity and fixed income components showing Sharpe ratios of 2.22 and 2.26, respectively. The benchmark followed closely, with Sharpe ratios of 2.49 for the total, 2.13 for equity, and 2.02 for fixed income.

Further insights can be derived by decomposing the total Sharpe ratio into risk contributions. The risk weight of the GPFG's equity portfolio averages approximately 77.9%, contributing a component Sharpe ratio of 2.36, while fixed income accounts for 22.1% of the risk, with a component Sharpe ratio of 3.15. In the benchmark, the equity share contributed about 74.9% of the risk (Sharpe ratio: 2.27) and fixed income 23.1% (Sharpe ratio: 2.83). This decomposition emphasizes the dominance of equities in driving both risk and return, while also showing the more stable Sharpe performance of fixed income over the long term.

METRIC	*GPFG Total*	*GPFG Equity*	*GPFG Fixed Income*	*Benchmark Total*	*Benchmark Equity*	*Benchmark Fixed Income*
AVERAGE RETURN	7.38%	9.19%	4.07%	7.06%	8.71%	3.78%
STANDART DEVIATION	2.75%	4.15%	1.80%	2.83%	4.09%	1.87%
AVERAGE TRACKING ERROR	1.22%	0.70%	0.91%	-	-	-
WEIGHTS	100%	55.0%	45.0%	100%	55.30%	44.70%
SHARPE RATIO	2.68	2.22	2.26	2.49	2.13	2.02
RISK WEIGHT	**-**	77.90%	22.10%	-	74.94%	23.06%
COMPONENT SR	**-**	2.36	3.15	-	2.27	2.83

Table 4: Summary of Return, Risk, and Performance Metrics for GPFG and Benchmark (1998–2024)

4.2 Brinson Hood Beebower Attribution Model:

The Brinson, Hood, and Beebower (BHB) geometric attribution model is applied to decompose the excess returns of the Government Pension Fund Global into allocation, selection, and interaction effects over the period 1998–2024. This analysis follows the methodology proposed by Burnie, Knowles, and Teder (1998) and further refined by Weber (2018). Over the full period, the GPFG achieved a total excess return of 6.00%, with the contributions from each component as follows: Allocation effect of -0.53%, Selection effect of 6.36%, and an Interaction effect of 0.20%. These results indicate that security selection was the dominant source of excess returns, while asset allocation slightly detracted from performance.

Several key periods reveal how the excess return evolved in times of market stress:

- 2008: Global Financial Crisis: The allocation effect was -0.10%, the selection effect was -4.65%, and the interaction effect was nearly neutral at 0.01%. These figures reflect the challenges faced by GPFG’s equity-heavy allocation during a period of severe market downturn.

- 2020: COVID-19 Pandemic: The allocation effect was -0.03%, the selection effect was 0.44%, and the interaction effect was negligible. This suggests relative resilience and highlights the importance of active security selection during a turbulent market, likely driven by strategic asset choices within each portfolio segment.

- 2022: War in Ukraine: The attribution effect was 0.12% for allocation, 0.59% for selection, and 0.17% for interaction. These positive results may indicate a well-timed and adaptive investment response, reflecting effective management under heightened geopolitical uncertainty.

Period	Fund Return	Total Excess Return	Allocation Effect	Selection Effect	Interaction Effect	Check
1998-2024 (Average)	7.38%	6.00%	-0.53%	6.36%	0.20%	0.00%
2008 (GFC)	-25.25%	-4.73%	-0.10%	-4.65%	0.01%	0.00%
2009 (GFC)	30.05%	3.51%	0.01%	3.50%	0.00%	0.00%
2020 (COVID-19)	14.18%	0.41%	-0.03%	0.44%	0.00%	0.00%
2022 (Ukraine War)	-15.66%	0.88%	0.12%	0.59%	0.17%	0.00%

Table 5: Summary of Brinson-Hood-Beebower (BHB) Geometric Attribution of GPFG Excess Returns (1998–2024)

To assess the long-term contribution of each component in the attribution framework, the chart below presents the cumulative geometric effects of allocation, selection, and interaction for the period 1998-2024, based on the geometric BHB attribution model.

While the table above provides a year-by-year breakdown for the most important years concerning geopolitical crisis, this cumulative analysis offers a more global view, highlighting which decision-making components have consistently driven or detracted from relative performance over time.

The selection effect emerges as the dominant driver of excess return creation, showing a substantial upward trend throughout the analysis period. Despite notable short-term volatility during the Global Financial Crisis (2008–2009), its overall trend remained positive, underscoring the importance of asset-specific decisions within each segment of the portfolio. In contrast, the allocation effect was modestly negative, indicating that the fund's top-down asset allocation decisions did not materially enhance returns and, on balance, slightly detracted from performance. The interaction effect, as expected, was relatively minor but marginally positive, with its most pronounced contribution observed in 2022, likely reflecting timely adjustments in the face of heightened geopolitical uncertainty.

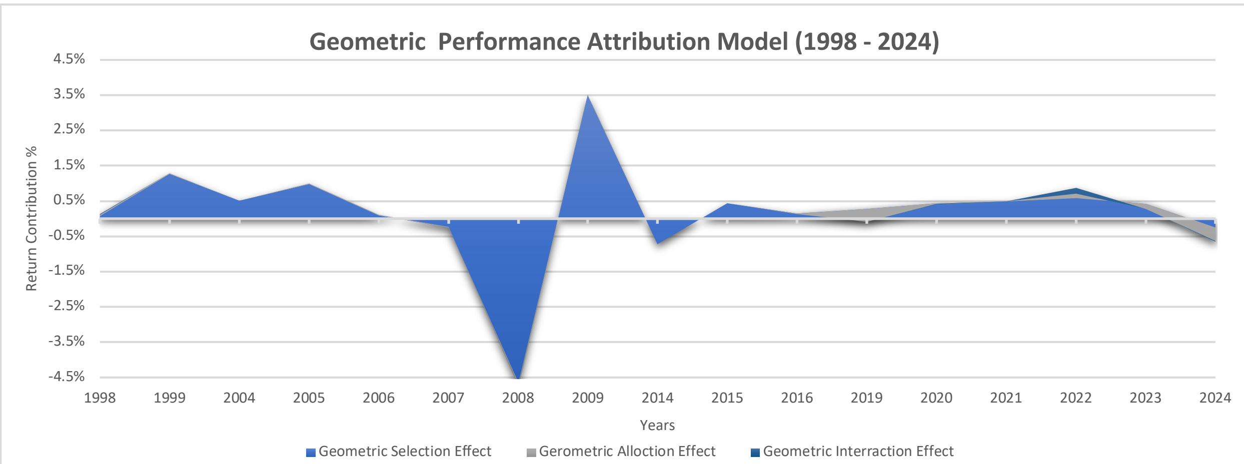

Figure 4: Annual Cumulative Geometric Performance Attribution Effects - Brinson, Hood, and Beebower (1998–2024)

The 2008 Global Financial Crisis (2007–2009), the 2020 COVID-19 pandemic (2019–2021), and the 2022 Ukraine War (2021–2024) are particularly relevant to this study. The decomposition of excess return shows significant changes across Allocation, Selection, and Interaction effects before, during, and after each crisis. In particular, the 2008 crisis stands out for the notable shifts in how these effects contributed to the fund's relative performance, shedding light on the GPFG's evolving response to market turbulence.

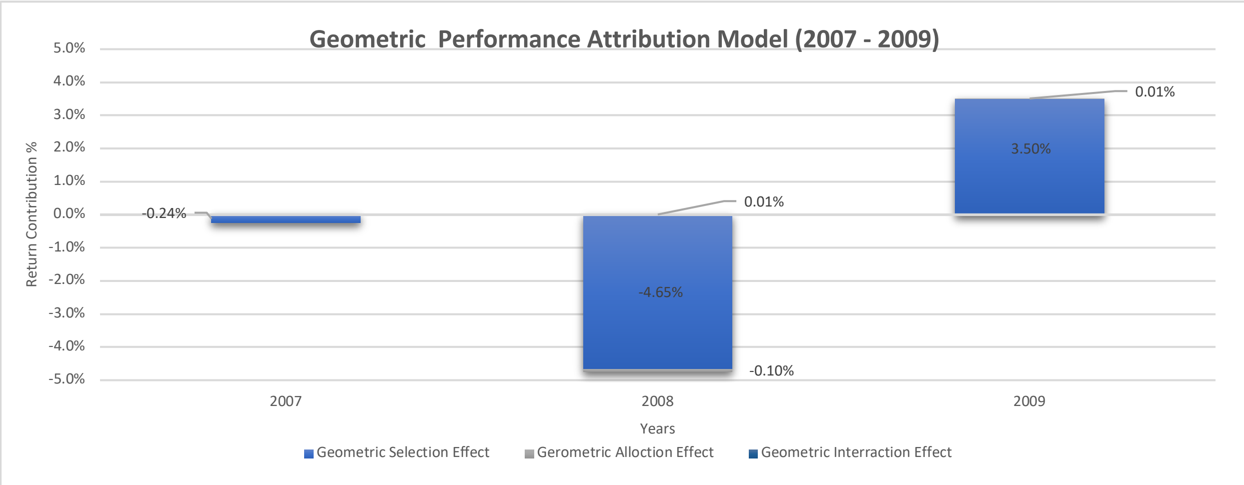

Figure 5: Annual Geometric Attribution Effects – GFC (2007 –2009)

From 2019 to 2021, the GPFG's performance attribution using the geometric BHB model shows relatively moderate shifts. Unlike the 2008 crisis, this period appears to be more manageable, with the Allocation effect briefly turning negative in 2019 but improving thereafter, while the Selection effect remained positive and stable. The Interaction effect stayed close to zero throughout the period.

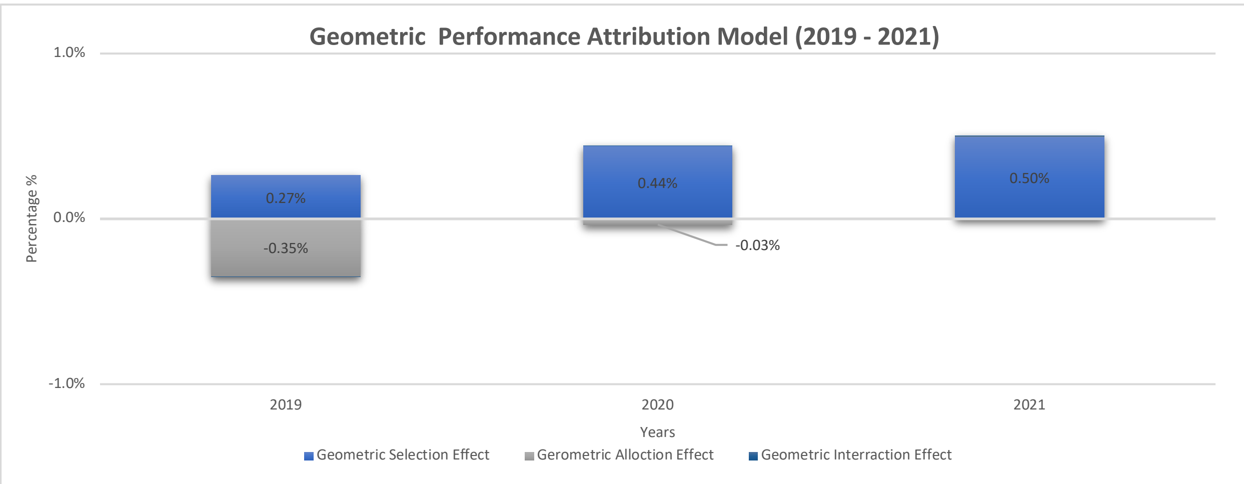

Figure 6: Annual Geometric Attribution Effects – COVID-19 Crisis (2019 –2021)

From 2021 to 2024, the GPFG's performance attribution shows more fluctuations compared to the COVID-19 period. The Allocation effect initially remained positive but turned negative by 2023 and 2024. Meanwhile, the Selection effect stayed positive through 2022 and 2023 but dropped significantly in 2024. The Interaction effect was generally negligible, with a slight increase in 2022

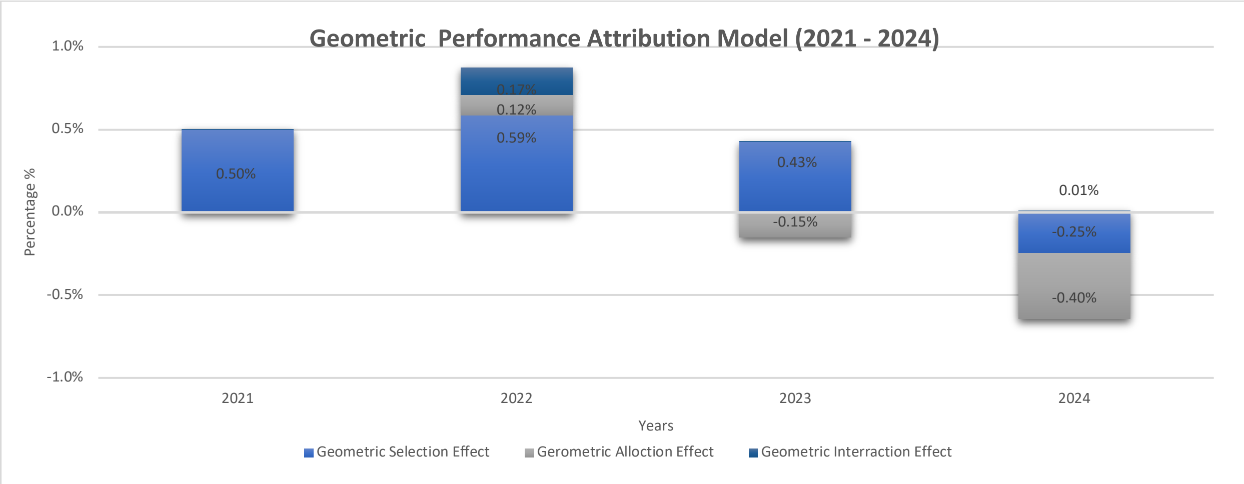

Figure 7: Annual Geometric Attribution Effects – Ukraine Invasion (2021 – 2024)

4.3 Factor-based Attribution Analysis

4.3.1 Factor Selection

For this study, the range of factors analyzed includes those used in the Fama and French 3-Factor model. This model improves the traditional Asset Pricing Model (CAPM) by including two additional factors that help explain the returns. The analysis also integrates a set of fixed-income factors to account for the specific risks and return drivers associated with the GPFG's Fixed-Income portfolio. These factors complement the equity framework and provide a more comprehensive understanding of the fund's multi-asset exposures.

- Market Risk (Market – Risk-Free Rate):

This measures the return of the overall market over the risk-free rate and captures the general risk associated with equity market exposure.

- Size Factor (SMB – Small Minus Big):

This factor captures the historical tendency of smaller-cap stocks to outperform larger-cap stocks, based on market capitalization.

- Value Factor (HML – High Minus Low):

This factor reflects the tendency of value stocks—those with high book-to-market ratios—to outperform growth stocks with low book-to-market ratios.

In simple terms, the three-factor model explains stock returns using market exposure, firm size, and the value-versus-growth orientation of a stock.

To improve the scope of the analysis, the extended Fama and French Five-Factor Model is also considered. This model introduces two additional factors that have been empirically shown to improve the explanatory power of return-based regressions:

- Profitability Factor (RMW – Robust Minus Weak):

This factor captures the tendency of firms with high operating profitability to outperform those with weak profitability, controlling for other variables.

- Investment Factor (CMA – Conservative Minus Aggressive):

This factor reflects the observed pattern in which firms that invest conservatively tend to outperform those that engage in aggressive expansion.

To address the second component of the portfolio, this study also incorporates four fixed income-specific factors: Investment Grade Corporate Bond Spread (IGCorp), High Yield Corporate Bond Spread (HYCorp), Term Premium (TERM), and Liquidity Premium (LIQ), while making use of the Bloomberg Investment Grade Factor Model. These factors are designed to capture key sources of systematic risk in fixed income markets: credit risk across both investment grade and high yield segments, interest rate risk through the term premium, and liquidity constraints via the liquidity premium. While the model only shows moderate explanatory power, this is consistent with the inherently more complex and heterogeneous nature of fixed income instruments. Nonetheless, the statistical significance of the results supports the relevance of these factors within a diversified portfolio's attribution framework.

- Investment Grade Corporate Bond Spread (IGCorp):

This factor captures the excess return required by investors for holding corporate bonds with high credit quality (typically rated BBB- or above) relative to risk-free government bonds. It reflects sensitivity to changes in perceived credit risk in the investment-grade segment.

- High-Yield Corporate Bond Spread (HYCorp):

This factor measures the spread between high-yield (non-investment grade) corporate bonds and risk-free government securities. It captures the compensation investors demand for taking on substantial credit risk, particularly relevant during periods of market distress or tightening financial conditions.

- Term Premium (TERM):

The term premium reflects the excess return that investors require for holding longer-term bonds instead of rolling over short-term instruments. It serves as a proxy for interest rate risk and the shape of the yield curve, both of which are relevant to the GPFG's fixed income strategy given its broad duration exposure.

- Liquidity Premium (LIQ):

This factor accounts for the additional return investors require for holding bonds that may not be easily tradable or are subject to market constraints. Given the fund's long investment horizon and its ability to hold less liquid instruments, this factor is particularly relevant to attempting to capture return dynamics in less efficient market segments.

The results obtained from the Fama and French 5-Factor Model indicate that the five key risk factors effectively capture the performance dynamics of the GPFG, though with varying degrees of explanatory power across the individual factors. The model demonstrates a strong explanatory power, as shown by an R^2 value of 0.84. This implies that approximately 84% of the variation in the fund's returns over the preliminary sample period of 2008–2024 can be attributed to these five factors, while the remaining 16% is likely explained by other influences not included in the model, possibly relative to fixed income. All the detailed regression results and model outputs are provided in Appendix B.

The most significant contribution comes from the Market Risk Premium, which exhibits a coefficient of 0.72. This suggests that for every 1% change in the overall market, the GPFG's return tends to move by approximately 0.72% in the same direction. The p-value associated with this factor is close to zero, confirming the strength and statistical significance of the relationship.

The second factor, corresponding to the size premium (SMB), displays a negative coefficient, indicating a slight tilt in the fund's strategy toward larger-cap firms. However, this relationship is not statistically significant, as its p-value exceeds the conventional 5% threshold.

The remaining three factors—value (HML), profitability (RMW), and investment (CMA)—exhibit relatively small coefficients accompanied by high p-values, all surpassing the level of statistical significance. These findings suggest that, during the observed period, these factors did not have a meaningful impact on the GPFG's return variation.

These preliminary results are based on a sample of 204 monthly observations, covering the period from 2008 to 2024.

In contrast, the application of the Fama and French 3-Factor Model, through the exclusion of the two statistically insignificant factors from the 5-Factor version, results in a modest improvement in explanatory power, with the R^2 increasing to 84.3%. Suggesting that approximately 15.7% of the variation in the GPFG's returns remains unexplained by the model and may be attributed to other sources, potentially including the fixed income segment of the portfolio.

All three retained factors exhibit p-values below the 5% threshold, indicating their statistical significance. Notably, the estimated coefficients for these factors are consistent with those observed in the 5-Factor model. This consistency supports the conclusion that the two additional factors in the extended model are redundant in this context and can be omitted without any loss of explanatory power. The results are presented in the Appendix B, table B2

4.3.2 Equity Factors

To assess whether the equity portfolio was the primary contributor to the unexplained portion of returns observed in the initial models, a separate linear regression was conducted using the Fama and French 3-Factor Model applied exclusively to the equity segment of the fund. The results reveal an even higher explanatory power compared to the full fund regression, with an R^2 of 0.89. This indicates that approximately 89% of the variation in the equity compartment's excess returns is explained by the three Fama-French factors. Moreover, the standard error of the regression is relatively low at 1.54%, suggesting a well-specified model with consistent residuals.

The regression coefficients can be interpreted as follows:

- **Intercept**: The intercept is negative and statistically significant at the 5% level ($\beta_0 = -0.0026$, $p = 0.0303$), implying that when all factors are equal to zero, the equity portfolio underperforms the risk-free rate by approximately 26 basis points per month. This underperformance may reflect tracking error, management costs, or other structural inefficiencies.
- **Market Risk Premium (X_1)**: The coefficient on the market factor is highly significant ($\beta_1 = 0.979$, $p < 10^{-81}$), indicating that the equity portfolio exhibits near-complete exposure to the market index. The confidence interval [0.924, 1.035] confirms the strength and reliability of this relationship.
- **Size (SMB, X_2)**: The size factor coefficient is negative and statistically significant ($\beta_2 = -0.097$, $p = 0.0408$), in contrast to the full-fund regression, where the size factor was not statistically significant. This finding suggests a slight bias toward larger-cap equities and an inverse exposure to the size premium.
- **Value (HML, X_3)**: The coefficient on the value factor is positive ($\beta_3 = 0.066$) but not statistically significant at the 5% level ($p = 0.061$). While this may suggest a small tilt toward value stocks, the 95% confidence interval includes zero, indicating that the result is not conclusive and should be interpreted with caution.

4.3.3 Fixed Income Factors

One important consideration remains regarding the inclusiveness of the selected factors. Although the R^2 obtained is already remarkably high, indicating a strong explanatory power for the fund's return in general, and the equity segment in particular, the models discussed so far primarily focus on equities, leaving a potential gap in representing the fixed income component of the GPFG.

To address this, a separate regression is performed for the fixed income segment over the whole period, this time starting with the Bloomberg Investment Grade Factor. The resulting R^2 of approximately 56.5% suggests a moderate level of explanatory power, which is expected given the more complex and often less factor-sensitive nature of fixed income instruments. The overall significance of the model is confirmed by an F-statistic of 52.93 and a corresponding low p-value.

The Bloomberg model includes the following five style-based risk factors:

- **Size**: Measures exposure to bonds issued by smaller versus larger firms.
- **Low Risk**: Captures exposure to lower-volatility bonds or higher-quality issuers.
- **Value**: Represents exposure to undervalued bonds trading at wider spreads relative to similar securities.
- **Momentum**: Reflects persistence in bond returns, where recent outperformers continue to perform well.
- **Multi-Factor**: A composite indicator summarizing the overall factor tilts of the portfolio relative to its benchmark.

Among these, two fixed-income sub-factors exhibit strong statistical significance. The size factor shows a negative and significant relationship with returns ($p < 0.005$), while the value factor is positively and significantly associated with fixed income performance ($p = 0.0005$). These findings suggest that while fixed income returns are more difficult to capture through linear factor models compared to equities, the Bloomberg framework offers valuable explanatory power and supports a meaningful decomposition of performance between the equity and fixed income components of the GPFG.

The regression analysis of the fixed income component using the Credit Premium yielded an R^2 value of only 9.26%, indicating that this factor explains only a minimal fraction of the variation in fixed income returns. This limited explanatory power suggests that the credit premium alone does not adequately capture the key drivers influencing the performance of the fixed income segment. Although the model may still be statistically significant overall, due to the large number of observations and the low p-value, the weak fit implies that other factors, such as macroeconomic conditions, liquidity constraints, bond duration, or issuer-specific characteristics are likely to have a more substantial influence on returns within the fixed income compartment.

The same analysis is applied to the Term Premium. The regression analysis of the fixed income component using the term premium as the explanatory variable produced an R^2 value of 7.95%, indicating that the term premium accounts for only a small portion of the variation in fixed income returns. While the model demonstrates limited explanatory power, the coefficient for the term premium remains statistically significant ($p < 0.05$). The positive coefficient (0.45) suggests that an increase in the term premium is generally associated with higher fixed income returns.

4.3.4 Extended Factors

To reinforce the robustness of the results, and to find which factors explain the rest of the returns, the regression analysis was extended beyond the standard Fama-French Three-Factor Model. Specifically, the Carhart Momentum Factor and the Fama-French Developed Markets Three-Factor Model were tested to evaluate whether these additional specifications could enhance the explanatory power of return variations in the GPFG. However, the inclusion of these alternative models did not yield statistically significant coefficients, nor did they contribute meaningfully to improving the explanatory strength of the regression.

The model incorporating the Momentum factor produced an R^2 of less than 0.03%, indicating a negligible contribution to the explanation of the fund's return dynamics. Similarly, the Fama-French Developed Markets Three-Factor Model achieved an R^2 of only 41%, significantly lower than the 84.3% obtained with the standard Fama-French Three-Factor Model.

Given these results, and in line with the principles of parsimony and model adequacy, it was concluded that the original three-factor model provides both statistically and economically meaningful explanatory power for the variation in the GPFG's equity returns. The findings confirm that neither the Momentum factor nor the developed markets version offers sufficient added value to justify their inclusion.

4.3.5 Final Selection of Risk Factors

To conclude this analysis, a final regression was conducted over the whole period, incorporating the most statistically significant factors identified throughout the study: the market return premium and the Bloomberg Investment Grade Factor. The linear regression of the total fund returns on the market excess return (Rm–Rf) and the Bloomberg Investment Grade Factor over the full period from 1998 to 2024 yielded strong and statistically robust results. The model achieved an R^2 of 79.54%, indicating that nearly 80% of the variation in the fund's returns can be explained by just these two variables. Both factors are highly significant, with p-values well below the 5% threshold, and the adjusted R^2 of 79.41% further confirms the model's explanatory strength, even after accounting for the number of predictors.

The estimated coefficients, 0.625 for the market factor and 0.498 for the investment grade factor, reflect meaningful and consistent contributions to the fund's overall performance. These results highlight that the combination of equity market exposure and investment-grade fixed income dynamics effectively captures the fund's primary sources of return.

While in theory, the inclusion of additional factors might improve the model's fit, further testing that incorporated the aggregated Fama and French 5-Factor Model, as well as other fixed income risk factors such as the term premium and credit premium, revealed that these added variables were not statistically significant at the 5% level across the full sample period. Although their inclusion led to a marginal improvement in the R-squared, their lack of significance justified their exclusion from the final Return-Based Style Analysis, in line with the principles of parsimony and exhaustiveness.

Regression Statistics	
Multiple R	0.89184614
R Square	0.79538954
Adjusted R Square	0.79411471
Standard Error	0.01458178
Observations	324

	Coefficients	*Standard Error*	*t Stat*	*P-value*
Intercept	-0.0002295	0.00083406	-0.2752011	0.78333878
IGcorp	0.62515355	0.05056143	12.3642383	5.5124E-29
Rm-Rf	0.49833786	0.01859348	26.8017592	6.8046E-84

Table 6: Regression Output: Market and Investment Grade Corporate Bond Factors – Total Fund (2008-2024)

Using the Fama and French 5-Factor Model alongside the Bloomberg Investment Grade Factor to explain the fund's returns only results in a marginal improvement in explanatory power. The model achieves an R-squared of 81.02%, a slight increase from the 79.54% obtained with only the Market Excess Return (Rm–Rf) and the Investment Grade factor. And despite this, only Rm–Rf and the Investment Grade factor remain statistically significant at the 5% level, with p-values well within the accepted significance levels.

In contrast, the additional factors from the five-factor model, SMB (size), HML (value), and CMA (investment), exhibit high p-values and are thus statistically insignificant in this context. While they contribute slightly to the overall R-squared, their weak individual significance limits their usefulness and interpretability within the model. Therefore, to maintain both parsimony and statistical robustness, these factors are excluded from the Return-Based Style Analysis (RBSA).

4.3.6 Simultaneity Bias

Another important methodological consideration is the potential for simultaneity bias, which occurs when explanatory variables are correlated with the regression error term. A common way to mitigate this bias is to lag the factor variables, regressing the fund's return at time *t* on factor values at time *t – 1*. However, in the case of the Government Pension Fund Global, this adjustment is neither necessary nor appropriate.

The GPFG maintains a continuous exposure to both global equity and fixed income markets through a mostly passive investment strategy, meaning that its returns are directly affected by contemporaneous market movements. This makes the use of current-period (non-lagged) factor returns, particularly the Market Excess Return (Rm–Rf) and the Bloomberg Investment Grade corporate bond index (IGCorp), both economically and empirically justified.

A statistical analysis further confirms this: while current Rm–Rf explains a significant portion of the monthly variation in fund returns ($R^2 > 79\%$), the explanatory power of a lagged Rm–Rf, using the prior month's return, is negligible. A similar pattern emerges for the IGCorp factor, where lagging the series causes a sharp drop in explanatory strength, indicating that the credit exposure influences return in real-time. These findings reinforce that the fund's performance reflects systematic market and credit sensitivity as it occurs, not with delay, aligning with the fund's non-tactical, long-term orientation.

Finally, because only two factors, the Market Excess Return and the Bloomberg Investment Grade factor, are both statistically significant and economically interpretable, there is no ambiguity regarding factor selection. This clarity eliminates the need for a Principal Component Analysis (PCA). As explained earlier in the analysis, PCA is typically used when many correlated factors must be reduced into orthogonal components to uncover latent structures. In this case, the model is already both parsimonious and grounded in financial theory, making PCA unnecessary.

4.3.7 Risk Exposure Stability during Market Crises

To evaluate changes in the GPFG's systematic risk exposure during periods of market stress, this study incorporates a crisis dummy variable (assigned a value of 1 for crisis periods: 2008–2009, early 2020, and 2022; 0 otherwise) along with interaction terms for the Market Excess Return (Rm – Rf) and the Bloomberg Investment Grade Corporate Bond (IGCorp) factors within the regression model ($R^2 = 79.6\%$). The results indicate no statistically significant shifts in risk exposure during crises, with interaction coefficients for Rm–Rf ($\beta = -0.019$, $p = 0.867$) and IGCorp ($\beta = 0.053$, $p = 0.279$). These findings suggest that the GPFG maintains relatively stable systematic risk profiles across turbulent market conditions.

4.3.8 Factor-Based Attribution Analysis

4.3.8.1 RBSA Factor Exposures

The RBSA was performed using the two statistically and economically significant factors identified in previous sections: the market risk premium (Rm–Rf) and investment-grade corporate bonds (IGcorp). On average, the portfolio exhibited a 50.1% exposure to Rm–Rf and 49.9% to IGcorp, compared to the benchmark allocation of 60% Rm–Rf and 40% IGcorp. This deviation in factor exposures is the basis for evaluating allocation and selection decisions.

The RBSA results, based on a rolling three-month window analysis and reported annually, present the following factor exposures and sum of squared errors (SSE) for key crisis and adjacent non-crisis years. In 2007 (non-crisis), the exposure to Rm-RF was 50.03%, IGCorp was 49.97%, with an SSE of 0.000074916. In 2008 (Global Financial Crisis), exposures shifted slightly to 50.51% (Rm-RF) and 49.49% (IGCorp), with a higher SSE of 0.000449521. In 2009 (non-crisis), exposures returned to 50.13% (Rm-RF) and 49.87% (IGCorp), SSE being 0.000110115. Similar stability was observed in 2019 (50.03% / 49.97%, SSE 0.000300502), followed by 2020 (COVID-19), with a minor change to 50.14% / 49.86% and a higher SSE of 0.000931864. In 2021, exposures were 50.01% / 49.99% (SSE 0.000457149); in 2022 (Ukraine War), they balanced at 50.00% each (SSE 0.001052793); and in 2023, exposure was 50.02% / 49.98% (SSE 0.000110828).

Overall, the results indicate that both the fund and benchmark maintained consistently stable exposures to the market (Rm-RF) and investment-grade corporate bond (IGCorp) factors across both crisis and non-crisis periods. Despite temporary increases in model error (SSE) during crisis years, the near-equal weightings suggest a consistent allocation approach and minimal variation in systematic factor exposure. This consistency supports the interpretation that observed return differences are more likely attributable to external shocks or transitory market effects rather than significant shifts in underlying portfolio strategy

4.3.8.2 Factor-based analysis results

The factor-based attribution model used in this study builds on the Brinson-Hood-Beebower (BHB) framework while incorporating some elements from Sharpe's (1992) Returns-Based Style Analysis and the multifactor asset pricing models developed by Fama and French (1993, 2015). The model is used to decompose the excess returns of Norway's Government Pension Fund Global over the period 1998 to 2024 into four key effects: Factor Allocation, Portfolio Allocation, Selection, and Interaction.

In 1998, for instance, the model reported a strong positive Factor Allocation effect (+1.04%) alongside a negative Selection effect (–1.32%), possibly reflecting the impact of the Russian debt default and the collapse of Long-Term Capital Management (LTCM), both of which heightened global systemic risk. By contrast, in 1999, the Selection effect turned strongly positive (+1.20%), potentially capturing gains from market recovery during the final stages of the dot-com boom.

During the Global Financial Crisis (2008–2009), the model highlighted different shifts. In 2008, all attribution components contributed negatively, with the Selection Effect (–1.93%), Allocation to the market return factor (–1.38%), and Allocation to the investment grade factor (–0.38%) being the most detrimental. However, performance recovered in 2009, with positive contributions across most effects, notably Allocation to Rm-RF (+0.95%), Allocation to IGCorp (+1.10%), and Selection Effect (+2.35%).

In 2014, during geopolitical tensions such as the annexation of Crimea and falling oil prices, the model showed modest positive contributions from Factor and Portfolio Allocation but negative Selection (–0.68%) and Interaction (–0.80%) effects. From 2015 onward, the attribution effects stabilized, showing fluctuations closer to zero, suggesting a more balanced approach in portfolio management or reduced deviation from the benchmark.

During the COVID-19 period (2020), the model showed varied attribution components. The Allocation effect to Rm-RF (+0.54%), Allocation to IGCorp (+0.40%), and Idiosyncratic effect (+0.14%) contributed positively, while the Selection Effect (–0.61%) was detrimental, with a minor negative Interaction Effect (–0.01%).

A more pronounced shift occurred in 2022, aligning with the turbulence following the pandemic's aftermath and the outbreak of the war in Ukraine. The Allocation to Rm-RF (+0.74%) and general Selection Effect (+2.04%) contributed positively, while Allocation to IGCorp (–0.54%) and to the Idiosyncratic effect (–1.52%) were detrimental, with a neutral Interaction Effect (0.00%).

In summary, the factor-based attribution results underscore the sensitivity of GPFG's performance to both strategic asset allocation and factor exposures, particularly during periods of global economic or geopolitical disruption. The use of only two factors, chosen for their statistical and economic relevance, ensures the model remains both parsimonious and robust. Consequently, there is no need for Principal Component Analysis (PCA) to reduce dimensionality, as the inclusion of both explanatory variables is justified.

Period	Excess Return	Allocation Rm-RF	Allocation IGCorp	Allocation idiosyncratic	Total Selection Effect	Interaction Effect	Check
1998-2024	8.63%	8.14%	8.51%	-1.58%	-6.44%	0.00%	0.00%
2008 (GFC)	-3.71%	-1.38%	-0.38%	-0.02%	-1.93%	0.01%	0.00%
2009 (GFC)	4.41%	0.95%	1.10%	0.00%	2.35%	0.00%	0.00%
2020 (COVID-19)	0.47%	0.54%	0.40%	0.14%	-0.61%	-0.01%	0.00%
2022 (Ukraine War)	0.72%	0.74%	-0.54%	-1.52%	2.04%	0.00%	0.00%

Table 7: Factor-Based Performance Attribution Summary for Crisis and Aggregate Periods (1998–2024)

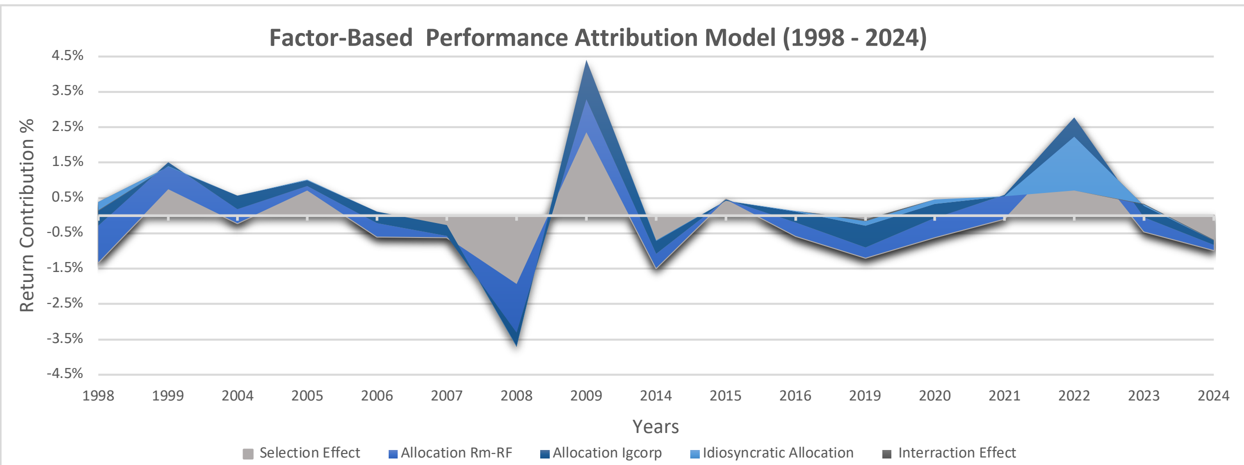

Figure 8: Cumulative Factor-Based Attribution Effects by Component (1998–2024)

During the 2008 Global Financial Crisis, the factor-based attribution analysis of the GPFG from 2007 to 2009 reveals significant volatility. The selection effects dropped sharply to –1.94% in 2008 before recovering to 2.35% in 2009, while the factor Allocation effects for Rm-RF and IGCorp shifted from –1.38% and –0.38% in 2008 to 0.95% and 1.10% in 2009, respectively. Aligning with a total excess return swing from –3.71% to 4.41%.

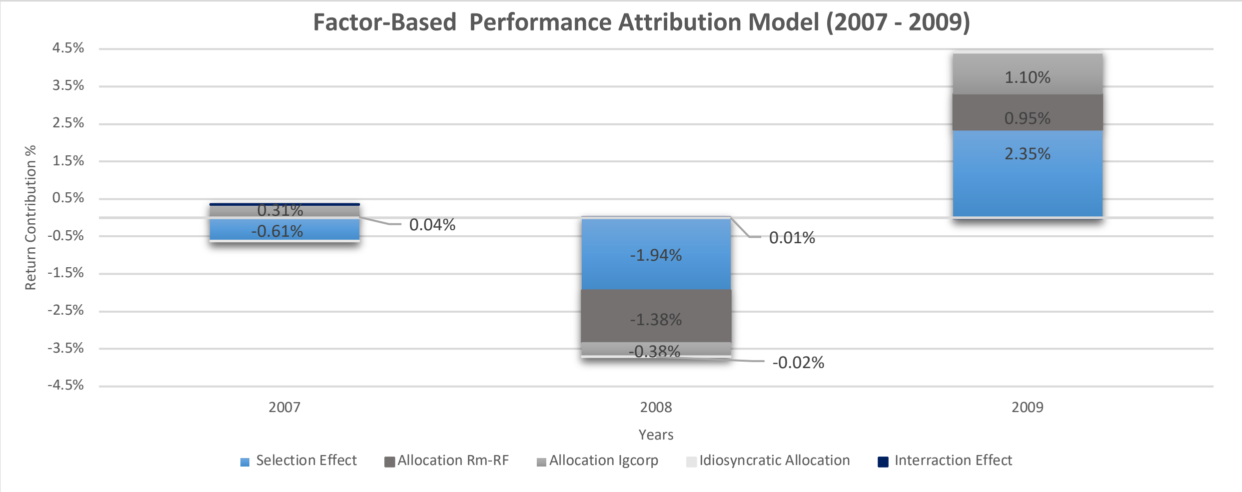

Figure 9: Cumulative Factor-Based Attribution Effects – Global Financial Crisis (2007–2009)

The factor-based attribution analysis of the GPFG from 2019 to 2021 during the COVID-19 pandemic reflects volatile performance across the components. The selection effects dropped to –1.19% in 2019 but gradually improved to –0.61% in 2020 and –0.08% in 2021. Meanwhile, the factor Allocation effects for Rm-RF remained consistently positive (ranging from 0.29% to 0.68%), whereas allocation for IGCorp shifted from 0.61% in 2019 to –0.04% in 2021. These patterns align with a recovery in total excess returns, moving from –0.10% to 0.55% over the period.

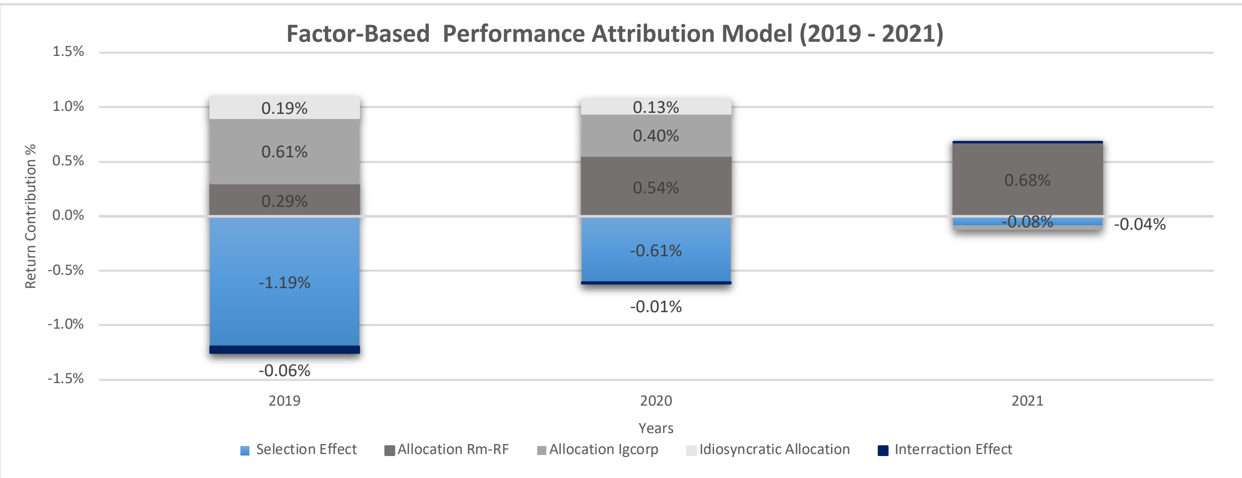

Figure 9: Cumulative Factor-Based Attribution Effects – Covid-19 Pandemic (2019–2021)

The factor-based attribution analysis of the GPFG from 2021 to 2024, covering the Ukraine War period, also reveals significant shifts, with Selection effects reaching a peak of 2.04% in 2022 before falling to -0.97% in 2024. The factor Allocation effects for Rm-RF are found to be consistently positive (ranging from 0.14% to 0.74%), while the allocation effect for IGCorp fluctuates from –0.54% in 2022 to 0.14% in 2024, aligning with a total excess return that moved from 0.55% to –0.69%.

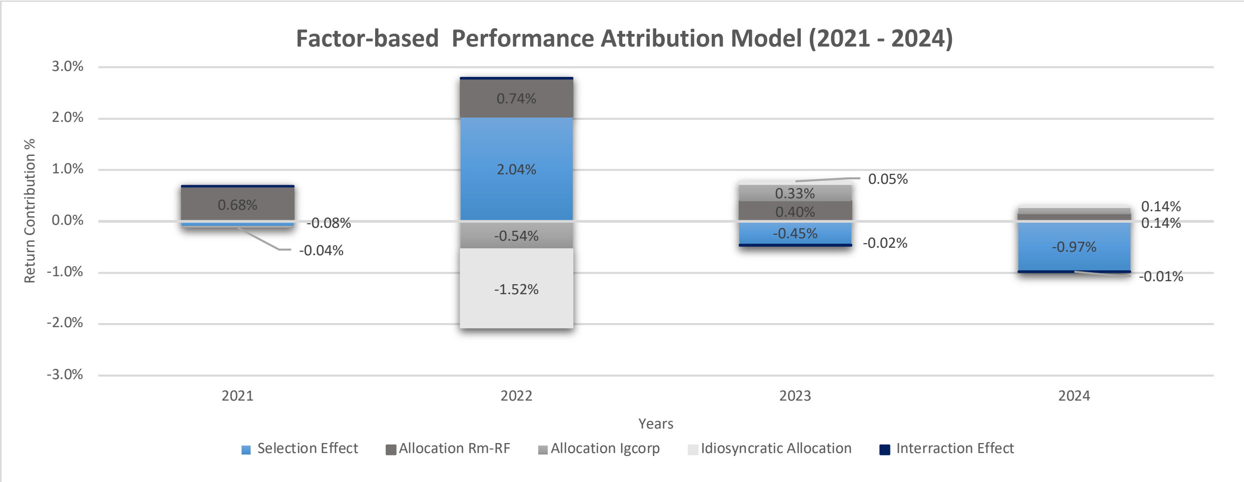

Figure 9: Cumulative Factor-Based Attribution Effects – War in Ukraine (2021–2024)

5. DISCUSSION

5.1 Overview

The empirical findings show that the GPFG achieved an annualized alpha of 0.79% relative to its benchmark. The GPFG's performance during turbulent periods highlights notable shifts when using the Geometric BHB and factor-based attribution models. In 2008, the Geometric BHB model shows a significant negative Selection effect (-4.65%) and a modest negative Allocation effect (-0.10%), while the factor-based model reveals substantial negative contributions from the market risk (-1.38%) and the Investment grade bonds factors (-0.38%) allocation effects, with a Selection effect of -1.94%. During 2020, the Geometric BHB model indicates a positive Selection effect (0.44%) despite a slight negative Allocation effect (-0.03%), whereas the factor-based model reflects positive Rm-RF (0.54%) and IGCorp (0.40%) allocations but a negative Selection effect (-0.61%). In 2022, the Geometric BHB model reports a positive Allocation effect (0.12%), a Selection effect of 0.59%, and a notable Interaction effect (0.17%), while the factor-based model shows a strong Selection effect (2.04%) offset by a negative IGCorp allocation (-0.54%) and a significant Idiosyncratic Allocation effect (-1.52%). These findings, to be interpreted later, underscore varying contributions across models during turbulent periods.

5.2 Interpretation of the Findings

5.2.1 Asset Allocation vs. Security Selection

The BHB attribution model reveals that security selection is the primary driver of the GPFG's excess returns, contributing about 6.36% over the study period, substantially outweighing the negative allocation effect of -0.53%. This result underscores NBIM's ability to identify and invest in high-performing securities within each asset class, particularly equities, which comprised approximately 70% of the portfolio as of 2024. The factor-based attribution model further supports this, showing that market exposure (Rm-Rf) accounts for approximately 70% of return variation, with selection effects driving significant contributions, such as 2.04% in 2022, despite challenges like -1.94% in 2008. GPFG's investment approach, combining passive market exposure with active strategies within strict risk parameters, enables the fund to avoid rigid benchmark replication and exploit idiosyncratic opportunities, as evidenced by positive selection effects across most years, including 0.44% in 2020 (BHB) and 0.75% in 1999 (factor-based).

In contrast, the negative allocation effect in the BHB model highlights limitations in top-down asset allocation decisions, with notable negative impacts of -0.10% in 2008 and -0.03% in 2020, reflecting the portfolio's overweight in equities (72.28% as of December 2024 per the benchmark, excluding real estate and infrastructure) relative to fixed income (27.72%). The factor-based model supports this finding, with negative allocation effects from Rm-RF (-1.38% in 2008) and IGCorp (-0.54% in 2022), suggesting potential difficulties in timing macroeconomic shifts or adapting to a rigid benchmark during geopolitical or market stress, such as the Global Financial Crisis, COVID-19 pandemic, and Ukraine War.

5.2.2 Factor-Based attribution model results

The factor-based attribution model provides a granular decomposition of the fund's excess returns, offering deeper insights into the sources of performance compared to the traditional Brinson-Hood-Beebower (BHB) model. While the BHB model attributes excess returns to broad categories, allocation, selection, and interaction effects. The factor-based model breaks down these effects into specific contributions from market (Rm-RF), investment-grade corporate bond (IGCorp), and idiosyncratic factors, as well as their respective allocation and selection effects. This detailed breakdown enhances the understanding of how specific factor exposures drive performance, particularly during periods of market stress such as the Global Financial Crisis (2008–2009), the COVID-19 pandemic (2020), and the Ukraine War (2022), as well as over the long-term period (1998–2024).

One key advantage of the factor-based model is its ability to isolate the contributions of specific risk factors. For instance, during the 2008 Global Financial Crisis, the BHB model shows a significantly negative selection effect, suggesting poor security selection relative to the benchmark. However, the factor-based model reveals that this negative performance was predominantly driven by poor security selection within the IGCorp factor, with a smaller negative contribution from Rm-RF selection. This specificity highlights that the fund's exposure to corporate bonds was particularly detrimental during the crisis, likely due to an increase in credit risk and market disruptions. In contrast, the BHB model's combined selection effect fails to show the relative impact of different asset classes, limiting its diagnostic power.

However, the fund experienced a strong recovery in 2009, achieving an excess return of 3.51%, almost entirely due to security selection (3.50%). This indicates that NBIM made effective bottom-up decisions during the recovery, successfully capitalizing on mispriced assets. Similarly, the factor-based model for 2009 showed positive contributions from both Rm-RF and IGCorp allocation and selection effects, suggesting the recovery was driven by a combination of strategic factor allocations and skillful security selection within those factors. While the BHB model also reflects a strong positive selection effect, it does not separate the impacts of market and corporate bond factors, offering less clarity on the specific sources of outperformance. Understanding this distinction is essential to determine whether the fund's recovery resulted from broad market rebounds or targeted corporate bond strategies.

During the 2020 COVID-19 period, the factor-based model highlights positive allocation effects from both Rm-RF and IGCorp, alongside a positive idiosyncratic allocation effect, suggesting that the fund benefited from tactical factor allocations. However, negative selection effects within both factors imply challenges in security selection. The factor-based model's ability to exactly find where these opposing dynamics lie provides a more refined view, revealing that while the fund's factor allocations were advantageous, its security choices within those factors underperformed.

For the 2022 Ukraine War period, the factor-based model identifies a positive allocation effect with regard to the market return factor and a strong positive IGCorp selection effect, in contrast with negative IGCorp and idiosyncratic allocation effects. This suggests that while the fund's market factor exposure was useful, its allocation to corporate bonds and idiosyncratic risks reduced the overall performance. The BHB model, in contrast, shows a positive allocation effect and a small selection effect, without isolating the specific factor-level dynamics, such as the significant positive contribution from IGCorp security selection.

Across these crises, security selection emerged as the consistent driver of positive excess returns, especially in recovery phases or during less challenging times. In contrast, allocation effects were either negative or negligible, underscoring the limitations of fixed benchmark structures in accommodating rapid, top-down strategic responses.

Over the long-term period (1998–2024), the factor-based model reveals that the fund's excess returns were driven primarily by strong allocation effects to the two factors, partially offset by a negative idiosyncratic allocation effect and a substantial negative selection effect for the fixed income factor. This shows that while strategic factor allocations were effective, security selection within corporate bonds consistently underperformed. The BHB model, while showing a strong positive selection effect and a negative allocation effect, does not clarify which asset classes or factors drove these outcomes, limiting its ability to guide portfolio adjustments.

The insights from the factor-based model are very useful for portfolio management. By decomposing returns into specific factor contributions, it enables portfolio managers to identify which factor exposures and security selections are driving outperformance or underperformance. This granularity supports more targeted factor changes and security selection strategies, particularly during crisis periods when factor dynamics can shift dramatically. For example, the negative selection effect on the fixed income factor in 2008 and 2020 suggests a need to reconsider corporate bond selection processes during market stress. In contrast, the BHB model's broad categories offer less clear guidance because they don't separate the effects of specific factors.

In conclusion, the factor-based attribution model adds significant value to the BHB model by providing a detailed, factor-specific decomposition of excess returns. Its ability to isolate market, corporate bond, and idiosyncratic contributions, along with their allocation and selection effects, offers deeper insights into the drivers of performance. This is particularly valuable during crisis periods, where understanding specific factor impacts can inform risk management and portfolio optimization. By contrast, the BHB model's aggregated approach, while useful for a high-level overview, lacks the precision needed for nuanced decision-making, making the factor-based model a critical tool for enhancing portfolio analysis and strategic allocation.

5.2.3 Comparing the Geometric BHB and Factor-Based Attribution Models results:

The Geometric BHB and factor-based attribution models, while both designed to break down the GPFG's excess returns, show different results in their allocation, selection, and interaction effects over the study period (1998–2024). In theory, the difference in returns, made up of these effects, should be similar between the two models, since they both analyze the same portfolio relative to the benchmark. However, the results suggest otherwise, especially in crisis years like 2008. That year, the Geometric BHB model shows a total excess return of -4.73% (with -0.10% from allocation, -4.65% from selection, and 0.02% from interaction), while the factor-based model reports -3.71% (with -1.38% from Rm-Rf allocation, -0.38% from IGCorp allocation, and -1.94% from selection).

One main reason for this difference is how each model calculates returns. The Geometric BHB model uses geometric compounding, which includes the effect of returns building on each other over time. In contrast, the factor-based model uses a simpler arithmetic method, adding returns directly. This difference in calculation can lead to big gaps in results, especially over long periods of time or during market stress, like in 2008, 2020, and 2022, when returns fluctuated sharply. Also, the factor-based model depends on linear factor exposures (like Rm-Rf and IGCorp), while the Geometric BHB model can better reflect complex portfolio behavior through its interaction term with the benchmark.

5.2.4 Factor Contributions

The factor-based analysis confirms that GPFG's returns are mainly driven by equity market exposure. The market risk premium (Rm-Rf) has a coefficient of approximately 0.5, showing the fund's sensitivity to stock market movements. This aligns with the fact that equity exposure explains about 70% of return changes in broader factor models. This sensitivity reflects the fund's current 70% equity allocation and its goal of long-term growth through broad market investment. The investment-grade corporate bond factor (IGCorp) has a stronger coefficient of 0.625 ($p < 0.01$), consistent with the fund's fixed income allocation, which was around 70% initially but has gradually decreased over time to about 27.72% in the benchmark, making room for increased equity investments.

For the fixed-income part of the portfolio, the Bloomberg Investment Grade Factor Model explains 56.5% of return variation, suggesting that while factors like size and value matter somewhat, more influential factors like macroeconomic trends and interest rate risk may have a bigger impact. Overall, the strong influence of equity-related factors highlights the fund's exposure to stock market fluctuations, raising concerns about risks during market downturns or global crises.

5.2.5 Benchmark Effectiveness

The effectiveness of GPFG's self-reported benchmark, structured with a strong bias toward U.S. markets (accounting for 57.10% of the equity benchmark), is a critical issue, especially during periods of sharp market stress. The benchmark's rigidity limited performance during crises, as illustrated by the negative allocation effects in 2008 (-0.10%) and 2020 (-0.03%). These results suggest that the fixed allocation failed to respond to rapidly evolving conditions, such as the global equity collapse in 2008 or the extreme volatility experienced during the COVID-19 pandemic.

Moreover, the heavy U.S. equity exposure inserted in GPFG's benchmark may have introduced a form of concentration risk, particularly visible during periods of geopolitical turbulence. The 2022 Ukraine War exemplifies this challenge. As sanctions against Russia and energy market dislocations reverberated through global asset prices, U.S. equity markets, though relatively separated geographically, were still impacted through energy supply chains, inflationary pressures, and risk-off investor behavior. GPFG's benchmark, with 57.10% of its equity allocation to U.S. markets, had limited capacity to turn away from these exposures, underscoring the inflexibility of fixed strategic asset allocations during crises.

While the benchmark serves a vital purpose in maintaining long-term consistency and reflecting GPFG's intergenerational wealth preservation mandate, it does not allow tactical changes in response to short-term risks. In contrast, NBIM's actual portfolio management showed greater agility. For instance, the divestment of Russian assets in early 2022, following the imposition of international sanctions, represented a politically and ethically motivated deviation from the reference index. Similarly, NBIM's adjustments to energy sector exposure may explain the positive allocation effect to the market exposure observed in 2022 (0.74%), suggesting that active management partially compensated for the benchmark's rigidity.

This pattern is not unique to 2022. During the Eurozone debt crisis (2011–2012) and the COVID-19 pandemic (2020), the GPFG also faced situations where rapid changes in macroeconomic conditions made the benchmark's fixed weights less appropriate. In 2020, for instance, despite GPFG's active selection helping reduce the impact of losses, the benchmark's inability to reflect sectoral shifts, such as the rotation into technology and healthcare stocks, meant that passive allocations missed key opportunities. These events reinforce a broader concern: geopolitical and systemic shocks often outpace the responsiveness of benchmark-driven strategies.

This tension raises important questions for sovereign wealth fund governance. On one hand, a rules-based benchmark provides accountability, transparency, and political insulation, which are critical for funds that manage public wealth. On the other hand, a framework that is too rigid may compromise resilience and value preservation in volatile environments. Traditional portfolio construction methods, often rooted in Modern Portfolio Theory (MPT), tend to underestimate the significance of geopolitical risk and liquidity constraints, with factors becoming increasingly critical for global funds navigating today's uncertain geopolitical landscape, which are increasingly relevant for global funds operating in uncertain geopolitical climates.

Consequently, there should be growing interest in hybrid benchmark models that keep long-term targets but allow conditional flexibility in asset weights based on macro indicators, geopolitical risk scores, or ESG triggers. For GPFG, future reform should not focus on abandoning the reference portfolio, but on improving it by adding optional, rule-based flexibility that lets managers respond wisely during global disruptions

5.3 Comparison with the current literature

The performance attribution analysis of the Government Pension Fund Global from 1998 to 2024, especially during turbulent market times, adds to the growing research on sovereign wealth funds. This study focuses on financial attribution using the Brinson Hood Beebower (BHB) model and Factor-Based Attribution, setting it apart from earlier studies that mostly look at SWFs from macroeconomic, governance, or geopolitical views. This thesis provides new insights into what drives GPFG's performance. The fund's ability to remain resilient during crises. and the limits of its benchmark give more context to these findings.

5.3.1 Active Management and Governance

The finding that security selection contributes 6.36% to GPFG's excess returns is consistent with Al-Hassan, Papaioannou, Skancke, & Sung (2013), who argue that sovereign wealth funds with independent and transparent governance structures are better equipped to engage in superior management strategies aimed at generating alpha, particularly in equity-heavy portfolios. Al-Hassan et al. (2013) suggest that funds like GPFG can leverage internal expertise to outperform benchmarks through security-level decisions, a pattern reflected in GPFG's positive selection effects of 0.44% in 2020 and 0.59% in 2022, showing resilience during the COVID-19 pandemic and the Ukraine War.

However, the negative selection effect of -4.65% in 2008 underscores the limitations of active strategies under conditions of systemic market collapse, suggesting that even well-governed SWFs may struggle to reduce the impact of losses during extreme downturns, especially that a negative allocation effect (-0.53%) has historically reduced GPFG's overall outperformance, particularly during crises when the benchmark's rigidity constrained timely reallocation.

These crisis-specific insights imply that while GPFG's governance framework supports effective active management in volatile periods, turbulent periods such as the 2008 Global Financial Crisis expose the vulnerabilities in equity-heavy portfolios, an important point less emphasized in the current literature with a broader focus on portfolio diversification and institutional design.

5.3.2 Financial Attribution vs Macroeconomic Focus

Unlike studies emphasizing macroeconomic or governance aspects of SWFs, such as Aizenman and Glick. While their academic work focusing on macroeconomic objectives explains the GPFG's equity-heavy mandate (70% allocation), it overlooks the fund's ability to generate alpha through security selection. In a similar way, Clark and Monk (2010) emphasize governance challenges, noting that SWFs face political pressures that constrain performance. In contrast, this study highlights GPFG's governance strength, as its adherence to the Santiago Principles enables controlled active management, particularly during the 2022 Ukraine War, where divestment of Russian assets contributed to a positive excess return (0.88%). By focusing on financial attribution, this thesis fills a gap in the literature, offering a performance-centric perspective that complements macroeconomic analyses.

5.3.3 Crisis Performance and Benchmark Rigidity

GPFG's crisis performance partially aligns with Bernstein & Al (2013), who argue that SWFs exhibit resilience in volatile markets due to long-term horizons. Their analysis of SWFS notes that some can recover through strategic rebalancing, consistent with the 3.50% selection effect for GPFG in 2009. However, this study's finding of negative allocation effects in 2008 (-0.10%) and 2020 (-0.03%) contests their findings, suggesting that benchmark rigidity and low tracking error can limit SWF's adaptability. This differs from Bodie and Brière (2014), who advocate dynamic benchmarks for institutional investors to navigate crises. GPFG's static benchmark (72.28% equity, 57.10% U.S. weighting) made outperformance during turbulent periods complicated. The positive allocation effect in 2022 (0.12%) suggests some improvement, possibly due to geopolitical adjustments such as the Russian asset divestment but underscores the need for further research into benchmark design for SWFs facing geopolitical shocks.

5.4 Benchmark Representativeness

The effectiveness of GPFG's self-reported benchmark in reflecting its investment strategy depends on how flexible it is, its ability to adjust to the fund's active management, and how well it represents the fund's main goals. As of December 2024, the benchmark allocates 72.28% to equities and 27.72% to fixed income (excluding real estate and infrastructure), with a large 57.10% of equities invested in U.S. markets (NBIM, 2024). This setup matches GPFG's goal of long-term growth by focusing on broad equity market exposure to preserve the wealth for future generations. However, the benchmark is quite rigid, which limits its flexibility. This was clear during crises like the 2008 Global Financial Crisis, the 2020 COVID-19 pandemic, and the 2022 Ukraine War. For example, negative allocation effects of -0.10% in 2008 and -0.03% in 2020 as seen in the Geometric BHB model analysis show how the benchmark's fixed structure restricted the fund's ability to quickly adjust to fast-changing markets, such as the equity market crash in 2008 or sector shifts toward technology and healthcare stocks in 2020.

Despite this rigidity, the benchmark still reflects GPFG's strategy by keeping a heavy focus on equities, consistent with the fund's 70% equity target and its long-term growth approach. The factor-based analysis also supports this, showing that the market risk premium (Rm-Rf) explains a large part of return variation, with a coefficient of 0.5 (Table 14). However, the benchmark's inability to adjust for active decisions, like the 2022 divestment from Russian assets, which added a positive allocation effect for the market 0.74%), means it doesn't fully show the fund's strategic flexibility. This difference is especially clear during geopolitical events, where NBIM's changes to energy sector exposure or ethical exclusions, like those following the Santiago Principles, differ from the benchmark's fixed weights. Also, the heavy U.S. equity focus adds concentration risk, as seen in 2022 when energy shocks and inflation affected U.S. markets, but the benchmark limited the options for shifting investments.

In summary, while the benchmark generally reflects GPFG's equity-focused, long-term investment approach, its lack of flexibility stops it from fully capturing the fund's active management and tactical responses to changing markets.

5.5 Implications for the different stakeholders

The performance attribution analysis of the Government Pension Fund Global over 1998–2024 provides great insights for sovereign wealth fund (SWF) managers, policymakers, and academics. The findings underscore the rigidity of GPFG's static benchmark, despite improvements in 2022 seen through the selection effect.

5.5.1 SWF Managers

For SWF managers, particularly those at Norges Bank Investment Management, the dominance of security selection underlines the value of active management within defined risk limits. Positive selection effect during the 2020 COVID-19 pandemic and the 2022 Ukraine War reflects NBIM's skill in identifying high-performing securities, even in volatile markets. To further enhance the alpha, managers should prioritize refining security selection processes, such as leveraging the use of advanced analytics (e.g., machine learning and AI for factor changes) or increasing exposure to undervalued sectors during crisis recoveries, as seen in 2009 with a 3.50% selection effect. However, the negative selection effect in 2008 of -4.65% highlights the challenges of active management during systemic crises, suggesting a need for robust risk management frameworks implementation to reduce downside risks in equity-heavy portfolios. Additionally, the negative allocation effects in 2008 and 2020 show that the GPFG's close tracking of the benchmark's allocation, which evolved from 70% bonds and 30% equity in 1998 to the opposite in 2024, limited flexibility in turbulent markets. Managers could explore strategies to increase tactical deviations within risk limits, such as temporary rebalancing during crises, to better align with the sudden market conditions while adhering to the GPFG's long-term mandate. These findings align with Ang, Goetzmann, and Schaefer (2009), who emphasize the GPFG's resilience through active management but do not address allocation constraints, highlighting an area for strategic improvement.

5.5.2 Policymakers

Policymakers, including those overseeing GPFG's mandate at the Norwegian Ministry of Finance, should potentially address the constraints of closely tracking the benchmark. This close adherence limited outperformance in 2008 and 2020, as the benchmark's fixed allocation within periods hindered adaptability to crises. Bodie and Brière (2014) advocate dynamic benchmarks that adjust to market volatility and geopolitical shocks, a recommendation directly applicable to GPFG. Policymakers can apply more frequent benchmark reviews to incorporate real-time risk factors, such as currency fluctuations or energy market disruptions, as seen in 2022's Ukraine War context (NBIM, 2022). Integrating geopolitical risk assessments, aligned with GPFG's adherence to the Santiago Principles, would enhance the benchmark's relevance during turbulent periods. Furthermore, policymakers could balance GPFG's intergenerational wealth preservation mandate with flexibility to capitalize on short-term opportunities, ensuring the fund remains resilient in future crises.

5.5.3 Academics

For academics, this study highlights several avenues for advancing SWF performance research. The non-significance of other Fama-French factors (e.g., SMB, HML) suggests that traditional models may not fully capture SWF-specific dynamics, particularly for funds with passive-leaning strategies like GPFG. Researchers should explore dynamic factor models, such as those using Kalman filters, to estimate time-varying exposures, especially during crises when GPFG's performance varied significantly (e.g., 2008 vs. 2020). Additionally, the impact of geopolitical risks, shown by GPFG's 2022 Russian asset divestment, allows for further investigation. Incorporating non-financial factors, such as ESG considerations or geopolitical indices, into attribution models could enhance explanatory power.

6. LIMITATIONS

A significant limitation is the available data from the NBIM reports, which include information on GPFG's holdings but not for individual securities. While data on individual equity and bond holdings are provided, their lack of detail (e.g., specific allocation percentages or weights for individual securities) limited this study's ability to conduct detailed attribution analysis of security selection decisions.

The study's attribution analysis was also limited by the assumption that GPFG's portfolio consisted of only two asset classes, equities and fixed income, with their weights summing to one, requiring adjustments to account for real estate and infrastructure holdings. These adjustments limited the ability to fully capture the performance contributions of real estate and infrastructure, particularly during crises like 2022, where such assets may have been influenced by geopolitical and energy market disruptions.

Finally, the lack of data on lesser-known factors, such as geopolitical risk, liquidity, or duration-specific factors, limited the ability to capture the dynamics of bond returns, which are particularly relevant for the GPFG's fixed-income allocation. These factors may have had a significant impact during crises, such as the 2008 financial shock, when the equity and bond market volatility was considerable, or in 2020, when monetary policy interventions influenced yields. In 2022, geopolitical risks, such as energy market disruptions, likely influenced returns, but this study lacks data on the factors to account for such non-financial risks. These data limitations may fail to capture the GPFG's adaptability in crises like 2020 and 2022, where active management reduced volatility. But future studies could incorporate dynamic factor models with time-varying exposures and include data on other bond-specific factors to better capture crisis-specific dynamics and improve attribution accuracy.

7. CONCLUSION

The analysis of the Government Pension Fund Global over the period 1998–2024 provides critical insights into the fund's performance attribution, particularly during major crisis episodes such as the 2008 Global Financial Crisis, the 2020 COVID-19 pandemic, and the 2022 Ukraine War. The results highlight Norges Bank Investment Management's consistent strength in security selection, which served as the primary driver of outperformance, especially during recovery periods in 2020 and 2022. However, the fund's close adherence to its self-defined benchmark, which evolved from a bond-heavy structure in 1998 to a predominantly equity-focused structure, limited its tactical responsiveness during extreme downturns, most notably in 2008, when a negative selection effect underscored the challenges of active management under systemic stress.

The factor-based analysis revealed that during crisis periods, such as the Global Financial Crisis, the COVID-19 pandemic, and the Ukraine War, GPFG's performance was heavily influenced by its equity market exposure, leading to significant challenges. The equity-focused strategy amplified losses in downturns, particularly due to sharp market declines, while the bond-related factors offered limited protection, as they struggled to capture the full impact of market stress and shifting risk dynamics. This underscores the fund's vulnerability to equity market volatility during crises and highlights the need for better tools to assess bond performance contributions in turbulent times.

This study contributes to the sovereign wealth fund (SWF) literature by providing a quantitative performance attribution perspective, which complements existing research focused on macroeconomic policy, governance frameworks, and strategic asset allocation. It builds upon prior work, which examined GPFG crisis resilience, especially quantifying the role of active management. And by explicitly quantifying the relative impacts of security selection and allocation, and highlighting the constraints imposed by fixed benchmarks during periods of market stress, this thesis adds a new empirical level to ongoing debates about SWF design and performance.

For stakeholders, the findings offer three main implications. First, SWF managers should continue refining active selection strategies, particularly in sectors sensitive to macroeconomic changes. Second, policymakers and central fund managers may benefit from exploring dynamic benchmark frameworks, which balance long-term objectives with crisis adaptability. Third, academics and financial modelers should consider prioritizing the development of more comprehensive factor models specific to sovereign wealth funds that incorporate not only equity and bond dimensions but also geopolitical risk, climate risk, and alternative asset classes such as real estate and infrastructure.

Future research could expand this framework by integrating ESG-sensitive factors, modeling real asset exposure, incorporating geopolitical risk indices, or applying machine learning techniques to detect dynamic patterns in factor exposures. Such enhancements would provide a better understanding of how sovereign wealth funds like the GPFG can maintain strategic stability while remaining tactically agile in a rapidly changing global landscape.

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9. APPENDICES

APPENDIX A: GEOMETRIC BHB ATTRIBUTION RESULTS (1998–2024)

Table A1: Geometric BHB Attribution Effects – Annual Summary (1998–2024)

Years	Differential Return	Geometric Allocation Effect	Geometric Selection Effect	Geometric Interaction Effect
1998	0.001	0.05%	0.07%	-0.01%
1999	0.014	0.02%	1.27%	0.00%
2000	0.002	0.01%	0.24%	0.00%
2001	-0.002	-0.26%	0.07%	0.00%
2002	0.004	0.01%	0.34%	0.00%
2003	0.006	0.01%	0.44%	0.00%
2004	0.006	0.00%	0.50%	0.00%
2005	0.010	0.01%	0.99%	0.00%
2006	0.001	0.00%	0.10%	0.00%
2007	-0.003	0.00%	-0.24%	0.00%
2008	-0.037	-0.10%	-4.65%	0.01%
2009	0.044	0.01%	3.50%	0.00%
2010	0.010	0.00%	0.96%	0.00%
2011	-0.001	-0.01%	-0.08%	0.00%
2012	0.002	0.04%	0.17%	0.00%
2013	0.010	0.12%	0.78%	0.00%
2014	-0.007	0.00%	-0.72%	0.00%
2015	0.004	0.00%	0.43%	0.00%
2016	0.001	-0.01%	0.14%	0.00%
2017	0.010	0.27%	0.57%	0.00%
2018	-0.004	0.08%	-0.50%	0.01%
2019	-0.001	-0.35%	0.27%	0.00%
2020	0.005	-0.03%	0.44%	0.00%
2021	0.006	0.00%	0.50%	0.00%
2022	0.007	0.12%	0.59%	0.17%
2023	0.003	-0.15%	0.43%	0.00%
2024	-0.007	-0.40%	-0.25%	0.01%

APPENDIX B: FACTOR-BASED ATTRIBUTION RESULTS (1998–2024)

Table B1: Regression Output: Fama and French 5 Factor Model (2008-2024)

Regression Statistics	
Multiple R	0.91782055
R Square	0.84239456
Adjusted R Square	0.83786567
Standard Error	0.01354089
Observations	204

	Coefficients	Standard Error	t Stat	P-value
Intercept	-0.0020949	0.00106209	-1.9724791	0.05013934
Market Risk	0.72337008	0.02532693	28.5612964	1.3793E-67
Size	-0.086922	0.04648198	-1.8700138	0.06316163
Value	0.0267075	0.04436498	0.60199507	0.54796104
Profitability	-0.0170989	0.05798741	-0.2948724	0.76844285
Investment Strategy	0.02513151	0.06628597	0.37913765	0.70504791

Table B2: Regression Output: Fama and French 3 Factor Model (2008-2024)

Regression Statistics	
Multiple R	0.91822595
R Square	0.84313889
Adjusted R Square	0.84046513
Standard Error	0.01343191
Observations	204

	Coefficients	Standard Error	t Stat	P-value
Intercept	-0.0021174	0.00103858	-2.0387298	0.0429729
Market Risk	0.72214757	0.02445868	29.5252018	4.3742E-70
Size	-0.0941212	0.04136709	-2.2752674	0.02409574
Value	0.02146034	0.03085379	0.6955495	0.48762838

Table B3: Regression Output: Fama and French 3 Factor Model – Equity Segment (2008-2024)

Regression Statistics	
Multiple R	0.94076467
R Square	0.88503817
Adjusted R Square	0.88307859
Standard Error	0.01535165

Observations	204

	Coefficients	*Standard Error*	*t Stat*	*P-value*
Intercept	-0.0025925	0.00118702	-2.1840493	0.03028127
Market Risk	0.97942624	0.02795441	35.0365492	2.8583E-81
Size	-0.0974347	0.04727944	-2.0608261	0.04079065
Value	0.06648479	0.03526353	1.88536976	0.06102772

Table B4: Regression Output: Bloomberg Investment Grade Factor – Fixed Income compartment (2008-2024)

Regression Statistics	
Multiple R	0.7516701
R Square	0.56500794
Adjusted R Square	0.54819832
Standard Error	0.02288644
Observations	204

	Coefficients	*Standard Error*	*t Stat*	*P-value*
Intercept	0.00289734	0.00190435	1.52143713	0.13008772
Size	-1.3774016	0.34707478	-3.9686018	0.00010814
Low Risk	0.59028978	1.46411553	0.40317159	0.68735034
Value	1.51571358	0.42683863	3.55102249	0.00050184
Momentum	0.6509946	0.3626175	1.79526526	0.07446409
Multi factor	0	0	65535	-

Table B5: Regression Output: Credit Premium – Fixed Income compartment (2008-2024)

Regression Statistics	
Multiple R	0.3042819
R Square	0.09258747
Adjusted R Square	0.08966034
Standard Error	0.01970313
Observations	204

	Coefficients	Standard Error	t Stat	P-value
Intercept	0.00272576	0.00112273	2.42779201	0.0157601
Credit Premium	1.02635641	0.18249191	5.62411996	4.1654E-08

Table B6: Regression Output: Term Premium – Fixed Income compartment (2008-2024)

Regression Statistics	
Multiple R	0.28202289
R Square	0.07953691
Adjusted R Square	0.07656768
Standard Error	0.01984431
Observations	204

	Coefficients	*Standard Error*	*t Stat*	*P-value*
Intercept	0.00288822	0.00112856	2.55920576	0.01096563
Term Premium	0.45484607	0.0878825	5.17561574	4.0905E-07

Table B7: Regression Output: Fama and French Developed Markets Three Factor Model – Equity compartment (2008-2024)

Regression Statistics	
Multiple R	0.64314712
R Square	0.41363822
Adjusted R Square	0.40364342
Standard Error	0.01412234
Observations	204

	Coefficients	*Standard Error*	*t Stat*	*P-value*
Intercept	-0.0007511	0.00108368	-0.6931263	0.48914391
Rm-Rf	0.25627523	0.02473657	10.3601766	6.1428E-20
SMB	0.07536243	0.06896557	1.09275436	0.27599515
HML	-0.1367426	0.04069584	-3.3601114	0.00095538

Table B8: Regression Output: Momentum Factor – Equity compartment (2008-2024)

Regression Statistics	
Multiple R	0.01730417
R Square	0.00029943
Adjusted R Square	-0.0053169

Standard Error	0.03371796
Observations	204

	Coefficients	Standard Error	t Stat	P-value
Intercept	0.0056596	0.00251906	2.24671243	0.02588715
Momentum	0.00969294	0.04197875	0.23090101	0.81765689

Table B9: Regression Output: Fama and French 5 Factor and Investment Grade Corporate Bond Factor – Total Fund (2008-2024)

Regression Statistics	
Multiple R	0.90011185
R Square	0.81020135
Adjusted R Square	0.80660895
Standard Error	0.01413241
Observations	324

	Coefficients	Standard Error	t Stat	P-value
Intercept	-0.0008041	0.00083253	-0.9658885	0.33483627
IGcorp	0.61002625	0.04962676	12.2922844	1.156E-28
Rm-Rf	0.53158494	0.02072196	25.6532163	2.4563E-79
SMB	-0.0044849	0.02939964	-0.1525492	0.87885084
HML	0.03623717	0.03162188	1.14595242	0.25267916
CMA	0.0672634	0.03717921	1.80916704	0.07137225
RMW	0.09166779	0.04731999	1.93718946	0.05361036

Table B10: Regression Output: Crisis Interaction effects – Total Fund (2008-2024)

Regression Statistics	
Multiple R	0.8923494
R Square	0.79628745
Adjusted R Square	0.79373306
Standard Error	0.01459529
Observations	324

	Coefficients	Standard Error	t Stat	P-value
Intercept	-1.1746E-05	0.00086529	-0.01357433	0.98917807
IGCorp	0.60670452	0.06714306	9.03599783	1.5984E-17
Rm-RF	0.48630299	0.0212	22.9388228	1.8081E-69
Rm-RF X Crisis Dummy	-0.01913411	0.11408007	-0.1677253	0.86690567

IGCorp X Crisis Dummy	0.05310161	0.04892655	1.0853332	0.27859362

APPENDIX C: RBSA (RETURNS-BASED STYLE ANALYSIS) WEIGHTS OVER TIME

Table C1: RBSA Results for GPFG – Annual Weights and Alpha (1998–2024)

Year	ß Rm-RF (%)	ß IGCorp (%)	Alpha (%)	GPFG Return (%)
1998	49.97%	50.03%	2.58%	5.96%
1999	48.89%	51.11%	-1.68%	1.76%
2000	43.75%	56.25%	-0.44%	-1.77%
2001	35.71%	64.29%	-0.05%	1.96%
2002	50.21%	49.79%	-0.89%	2.28%
2003	48.73%	51.27%	-0.63%	2.11%
2004	49.96%	50.04%	1.51%	2.66%
2005	48.07%	51.93%	-0.25%	-1.92%
2006	49.32%	50.68%	0.36%	2.21%
2007	49.79%	50.21%	1.25%	2.99%
2008	40.95%	59.05%	-2.26%	-15.26%
2009	54.62%	45.38%	0.48%	-0.49%
2010	48.18%	51.82%	0.74%	2.79%
2011	48.62%	51.38%	1.10%	7.42%
2012	51.74%	48.26%	0.66%	0.32%
2013	50.30%	49.70%	0.15%	2.95%
2014	50.71%	49.29%	-1.71%	0.01%
2015	49.13%	50.87%	0.79%	4.88%
2016	55.60%	44.40%	-0.53%	-2.15%
2017	50.64%	49.36%	-0.32%	1.04%
2018	49.76%	50.24%	-1.55%	-5.95%
2019	48.48%	51.52%	1.50%	2.55%
2020	56.11%	43.89%	-0.50%	-1.73%
2021	50.72%	49.28%	-0.21%	3.19%
2022	53.24%	46.76%	-0.01%	3.44%
2023	54.28%	45.72%	-0.31%	-2.73%
2024	50.87%	49.13%	-1.43%	-3.09%

Table C2: RBSA Results for the Self-Reported Benchmark – Annual Weights and Alpha (1998–2024)

Year	ß Rm-RF	ß IGCorp	Alpha	GPFG Return
1998	49.97%	50.03%	2.57%	5.92%
1999	48.89%	51.11%	-1.71%	1.67%
2000	43.75%	56.25%	-0.41%	-1.55%
2001	35.71%	64.29%	-0.05%	1.83%
2002	50.21%	49.79%	-0.89%	2.31%
2003	48.73%	51.27%	-0.63%	2.02%
2004	49.96%	50.04%	1.50%	2.65%
2005	48.07%	51.93%	-0.24%	-1.89%
2006	49.32%	50.68%	0.36%	2.19%
2007	49.79%	50.21%	1.16%	2.89%
2008	40.95%	59.05%	-2.04%	-14.23%
2009	54.62%	45.38%	0.47%	-0.65%
2010	48.18%	51.82%	0.73%	2.71%
2011	48.62%	51.38%	1.09%	7.27%
2012	51.74%	48.26%	0.65%	0.26%
2013	50.30%	49.70%	0.15%	2.96%
2014	50.71%	49.29%	-1.65%	0.07%
2015	49.13%	50.87%	0.78%	4.81%
2016	55.60%	44.40%	-0.61%	-2.27%
2017	50.64%	49.36%	-0.32%	1.05%
2018	49.76%	50.24%	-1.55%	-5.92%
2019	48.48%	51.52%	1.43%	2.45%
2020	56.11%	43.89%	-0.53%	-1.87%
2021	50.72%	49.28%	-0.21%	3.24%
2022	53.24%	46.76%	-0.01%	3.72%
2023	54.28%	45.72%	-0.32%	-2.80%
2024	50.87%	49.13%	-1.37%	-3.03%

APPENDIX D: EVOLUTION OF GPFG ASSET CLASS WEIGHTS (1998–2024)

Table D1: Annual Weights of GPFG Equity and Fixed Income Holdings (% of Total Portfolio)

Year	Equity (%)	Fixed Income (%)
1998	0.306	0.694
1999	0.405	0.595
2000	0.412	0.588
2001	0.402	0.598
2002	0.396	0.604
2003	0.407	0.593
2004	0.414	0.586
2005	0.404	0.596
2006	0.406	0.594
2007	0.425	0.575
2008	0.504	0.496
2009	0.571	0.429
2010	0.609	0.391
2011	0.599	0.401
2012	0.602	0.398
2013	0.632	0.368
2014	0.619	0.381
2015	0.635	0.365
2016	0.622	0.378
2017	0.673	0.327
2018	0.667	0.333
2019	0.671	0.329
2020	0.692	0.308
2021	0.733	0.267
2022	0.636	0.364
2023	0.709	0.291
2024	0.698	0.302

APPENDIX E: ANNUAL RISK FACTORS RETURNS (1998-2024)

Table E: Annual Risk Factor returns (1998-2024) (% of Total Portfolio)

Year	Rm-RF (%)	LUACER Index / IGCorp (%)
1998	19.79%	7.20%
1999	19.06%	-1.49%
2000	-16.49%	8.53%
2001	-13.70%	9.73%
2002	-23.27%	13.08%
2003	27.50%	7.87%
2004	10.45%	5.25%
2005	3.30%	2.30%
2006	9.91%	4.33%
2007	1.40%	4.21%
2008	-44.19%	-5.24%
2009	27.40%	18.11%
2010	17.89%	8.48%
2011	1.70%	7.78%
2012	15.70%	10.25%
2013	30.87%	-4.65%
2014	11.48%	7.06%
2015	0.90%	-0.60%
2016	13.11%	6.05%
2017	19.58%	6.29%
2018	-5.88%	-2.98%
2019	25.61%	13.82%
2020	24.83%	9.69%
2021	21.81%	-0.94%
2022	-21.24%	-15.94%
2023	20.09%	8.46%
2024	18.00%	3.81%

EXECUTIVE SUMMARY

This thesis analyzes the performance of Norway's Government Pension Fund Global (GPFG), the world's largest Sovereign Wealth Fund, over the period 1998 to 2024. It explores how the fund performed in both stable periods and during major market disruptions, namely the 2008 financial crisis, the 2020 COVID-19 pandemic, and the 2022 Ukraine War. Two analytical approaches are used: the Brinson-Hood-Beebower (BHB) model, which breaks down the relative performance into the impact of asset allocation (choosing between asset classes like stocks and bonds) and security selection (choosing specific investments); and Factor-Based Attribution, which identifies return drivers such as exposure to market trends or bond-related factors.

The results show that security selection played the largest role in generating excess returns relative to the self-reported benchmark. In contrast, asset allocation had a smaller, and at times negative, effect due to the fund's close alignment with its strategic benchmark. During crises, performance was mixed. For instance, in 2008, losses in certain sectors may have been linked to sanctions or concentrated exposures, while strategic selections during the 2009 recovery contributed to strong gains.

This research adds to the understanding of Sovereign Wealth Funds by connecting investment outcomes with global market events. It provides a useful framework for evaluating performance and highlights the importance of active decision-making in the context of sovereign wealth funds. The findings suggest that refining security selection, adapting benchmarks in response to crises, and factoring in global risks, especially in bond markets, can help funds like GPFG navigate uncertainty and safeguard long-term national wealth.

MOTS-CLÉS/KEYWORDS: Sovereign Wealth Funds, Performance Attribution, Government Pension Fund Global, Brinson-Hood-Beebower Model, Factor-Based Analysis, Geopolitical Risk, Benchmarking

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Ecole de Gestion de l'Université de Liège