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Risk, Return, Responsibility – Inclusion of ESG Criteria in a Portfolio Optimization Framework

Master Thesis in Banking and Finance

Pascal Zuber

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Executive Summary

Institutional investors, mainly in the pension fund sector, increasingly account for non-financial criteria such as environmental, social and governmental (ESG) factors when it comes to portfolio optimization. Yet, many investors are reluctant to incorporate responsible investment considerations quantitatively in the sense of accounting for a set of criteria that figure as input in a portfolio construction and management process on equal terms with risk and return. Instead, sheer screening methods are prevalent in the industry, where some sort of exclusionary filtering takes place in the first stage, followed by common portfolio management according to mean-variance criteria. In fact, there is a shortage of adequate methods to consider ESG factors integrally. The present thesis rationalizes quantitative integration of ESG measures in portfolio management and discusses existing approaches in the literature, a majority of which is set in the area of Multiple Objective Optimization. It then suggests a novel method based on the Black Litterman model. The suggested framework imposes a structure on the covariance matrix to effectuate weight shifting according to single ESG scores of the portfolio members. Moreover, it enables the investor to calibrate the degree of ESG incorporation and allows for incorporating views on financial performance. The effects of the method on portfolio weights are analyzed empirically. In an out of sample analysis, the weight shifted portfolios generated by implementing the suggested method are shown to exceed the benchmark in terms of portfolio ESG scores. One of the three variations of the suggested method is able to outperform the market in terms of financial performance for the period in consideration.

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Acronyms

ARA Absolute Risk Aversion.

AVM Adjusted Variance Method.

BLM Black-Litterman Model.

CAL Capital Allocation Line.

CAPM Capital Asset Pricing Model.

CSR Corporate Social Responsibility.

EFAMA European Fund and Asset Management Association.

EFFAS European Federation of Financial Analysts Societies.

ESG Environmental, Social, Governmental.

Eurosif European sustainable investment forum.

EVE Expected Value at the End of the Period.

GSIA Global Sustainable Investment Alliance.

IQIE Integral Quantitative Integration of ESG-criteria.

IR Information Ratio.

MCDA Multiple Criteria Decision Analysis.

MOOP Multi-Objective Optimization.

MPF Market Portfolio.

MPT Modern Portfolio Theory.

MV Mean-Variance.

NFP Non-Financial Performance.

RI Responsible Investment.

RIAA Responsible Investment Association Australasia.

SMI Swiss Market Index.

SR Social Responsibility.

TE Tracking Error.

UKSIF UK Sustainable Investment & Finance Association.

UNPRI United Nations principles for responsible investment.

USSIF US Forum for Sustainable and Responsible Investment.

VNM Von Neumann Morgenstern.

Introduction

In this chapter the core motives for choosing the subject of quantitative integration of responsibility into portfolio construction and management is discussed, a short literature review on current works tackling the same subject is given and the structure of the thesis is outlined.

1.1 Motivation and Goal

Responsible Investment (RI) has overcome the stage of being a niche phenomenon in financial academia as well as in the industry during the last decade and it will most likely become more important in the future (e.g. Renneboog et al. (2008b), Eurosif (2014), KPMG (2015)). The question of how to address Environmental, Social, Governmental (ESG) criteria within the investment process is vital and there is not a single right answer to it. Rather, there are several approaches considered by institutional investors, investment banks or private asset managers to include ESG criteria along the investment process. The present Master's Thesis focuses on the strategy of *integration*, which by both, the European sustainable investment forum (Eurosif) ¹, as well as the United Nations principles for responsible investment (UNPRI)² is categorized as explicitly including ESG factors systematically into traditional financial analysis and investment decisions (Eurosif (2014), UNPRI (2016))(cp. table D.1 in Appendix D). Within the strategy of integration, the present thesis nar-

¹ The Eurosif is a network of of financial service providers and investors promoting RI in the European market.

² The UNPRI is - similar to the Eurosif - a global stakeholder network with the purpose of establishing principles of responsible investments across the industry.

rows down the scope further on approaches that involve ESG measures quantitatively in portfolio construction, selection and management. This is achieved by means of expanding a conventional portfolio optimization process known from financial practice and literature considering at least one additional ESG-linked criterion in some form. According to Eurosif (2014) the strategy of systematic integration is underrepresented in European markets as compared to other strategies like exclusion or screening. A recent survey on RI Funds in Europe (KPMG, 2015) states that besides the demand growing for RI in general, investors increasingly request their asset managers for ESG-integration to a higher degree. This might emerge out of the commitment of mainly institutional investors to ESG-factor integration. In fact, institutional investors such as pension funds or insurance companies align themselves increasingly with ESG integration, either by regulatory impulses or by in-house investment policies (e.g. Wood et al. (2013), Renneboog et al. (2008a), Waddock (2008)). Yet, there are still impediments and also misconceptions of what is the best investment practice in order to serve the beneficiaries. Closely related to this matter, there is evidence of a predominance of Modern Portfolio Theory (MPT) based approaches in an institutional investors context (Juravle and Lewis, 2008). This predominance combined with the lack of appropriate methods is deemed a substantial barrier to include ESG factors in the core portfolio management process. Thus, there seems to be a potential need for systematic integration of ESG considerations in an approach that combines MPT principles with ESG factors as addressed with this Master's Thesis. This reasoning is substantiated by Von Wallis and Klein (2015) or Capelle-Blancard and Monjon (2012) who provide an overview on RI-literature and remark that further research is necessary in the direction of conceptual work, framing how to integrate RI-considerations into portfolio optimization. The present thesis aims at illuminating existing approaches in current literature to quantitatively integrate ESG factors along with volatility and return in a portfolio management process and proposes a novel approach based on the Black Litterman portfolio optimization framework.

1.2 Contribution and Limitations

This Master's Thesis contributes to the literature in scrutinizing different possibilities of the inclusion of ESG criteria in a quantitative portfolio optimization context. Neither has such a review nor the

proposed Black Litterman based method been offered so far, to the best of the author's knowledge. It is not the goal of the thesis to list and describe every single published method coping with ESG oriented portfolio optimization, but to provide a representative selection to catch different starting points to approach this problem. Also beyond the scope of the study would be the development of a proprietary quantification of ESG factors; for this purpose, an external database is used.

1.3 Literature Review

ESG concerns in an investment context have been increasingly in the focus of academic literature since the turn of the millennium and, even to a higher degree since the financial crisis in 2007. However, RI research history reaches back even further. For a comprehensive and well documented literature review of RI in general see e.g. Von Wallis and Klein (2015) or Capelle-Blancard and Monjon (2012) on trends in RI literature as well as Viviers and Eccles (2012) for a retrospect on 35 years of RI research. The vast majority of the papers address the question of the financial performance of RI compared to conventional investments (see e.g. Capelle-Blancard and Monjon (2012)). In relation to that, there are relatively few works that aim at the incorporation of ESG criteria into portfolio optimization. However, there is a growing body of literature to do so. Utz et al. (2014) cover a tri-criterion Mean-Variance (MV) Optimization approach based on a Von Neumann Morgenstern (VNM) utility function setup. In their method, assets are assigned an ESG-score in addition to expected return and volatility, such that efficient portfolios are to be found on a non-dominated surface rather than the efficient frontier. Ballesterio et al. (2012) split the asset universe into subsets of ethical assets and assets not considered as ethical and apply a VNM setup to minimize deviations from expected utilities according to investor dependent financial and ethical goals. In Hallerbach et al. (2004) a two-stage approach is elaborated to meet investor preference based on a multitude of asset attributes. A set of feasible portfolios fitting the investor's constraints are calculated, then a final portfolio is selected in an interactive multiple goal programming framework. Lundström and Svensson (2014) apply a multi criteria decision making approach by extending the traditional MV framework by an ESG criterion. They propose two methods: the weighted sum approach minimizing the sum of weighted objective functions subject to a set of constraints, and the ϵ -constraint truncating

the feasible set by imposing constraints to do so. Bilbao-Terol et al. (2012) apply a fuzzy logic approach in combination with multiple goal programming to account for additional ESG goals. In Drut et al. (2010) non-financial criteria are accounted for in an additional constraint to a common MV framework. Jessen (2012) tackles the problem of ESG integration from a utility centered perspective. In Dorfleitner and Utz (2012) and Dorfleitner et al. (2012) ESG is considered within a *sustainable return* framework, adopting the concept of stochastic financial returns to the non-financial level. Brandstetter and Lehner (2015) propose an adaptation of the Black-Litterman portfolio optimization model that incorporates a social and environmental impact score besides conventional inputs to the model. However, the present thesis contributes to the literature independently, since the two approaches differ in a substantial way. A more detailed review of existing literature is given in Chapter 3.

1.4 Structure of the Thesis

In chapter 2, major concepts and definitions in the field of RI are discussed and the respective market is described. Furthermore, a rationale for RI in general is elaborated. Chapter 3 discusses the rationale of quantitative integration of ESG considerations in particular. It then describes and compares a selection of approaches that include ESG measures quantitatively and systematically in the portfolio construction process. In chapter 4 a novel method to integrate ESG factors in an equity focused Black-Litterman portfolio optimization context is developed. Chapter 5 empirically tests the proposed method and analyzes the performance of applying the method in comparison with a benchmark. Chapter 6 concludes.

Responsible Investments

To set a basic frame for the thesis, the sections of this chapter discuss the field of RI by outlining its elementary concepts and definitions, characterizing the corresponding market and investment strategies. Also, the chapter sheds light on ESG-ratings and discusses the inclusion of such measures in financial decision making. It concludes with a reasoning for investing in RI.

2.1 Basic Concepts

As RI is a relatively young phenomenon in academic literature as well as in a practitioners context, there is a plurality of concepts and definitions and a lack of consensus. Sandberg et al. (2009) detect heterogeneity on the levels of terminology, definitions, strategy and practice of RI across publications through different cultures and discuss whether standardization is desirable or even feasible. Similarly, as Eccles and Viviers (2011) put it, there is some sort of conceptual fuzziness since some terms might be used synonymously and some might be polysemic. On the definitional level, terms are often used interchangeably. Whether it is called ethical investment, socially responsible investment (SRI), responsible investment or sustainable investment, there seems to be at least a basic common denominator that most of the definitions are in line with. Elementary to these conceptions is the integration of specific non-financial concerns (Sandberg et al., 2009) into the investment process. These concerns are typically referred to as environmental, social and governmental (ESG). Depending on the semantic context, the use of either of the definitions stresses a different property of RI.

For example *sustainable investment* emphasizes the long-term orientation, while *socially responsible investment* might point at a desirable behavior in a socio-ethical context. Also, definitions and respective connotations depend on their historical background. The term *ethical* in that specific context might link to early uses of ethical investments fostered by churches as Quakers and Methodists in U.S., U.K. and Australia (Sparkes and Cowton, 2004). An accurate definition is formulated by the United Kingdom Social Investment Forum (UKSIF), stating that socially responsible investments are investments that allow for the combination of both financial objectives and social values of investors (Muñoz-Torres et al., 2004). In this thesis the term *responsible investment (RI)* is used for the sake of neutrality and in order to avoid emphasizing only one of the ESG factors.

Describing RI terminology, one has also to be aware that catch-all terms like the above mentioned are prone to being used for labeling investment products that follow all sorts of strategies. Notions like *ethical investment* or *socially responsible investment* might evoke the impression of maintaining moral integrity while investing in financial vehicles. However, the degree of what could be perceived as moral integrity differs largely from strategy to strategy, from fund to fund and not least on how moral integrity is defined. For one investor the exclusion of alcohol manufacturers from the asset universe might be morally appropriate, for another one avoiding investments in companies linked to child labor might be so. This divergence of perceptions is likely one of the reasons, why the lack of standardization is still an issue across the industry. Similar to the subject of moral integrity, Hellsten and Mallin (2006) raise the - in itself ethical - question whether being invested in ethical funds is a way to participate in the capital markets without bearing responsibility for promoting inequality between the rich and the poor. Moreover, it is scrutinized in the same paper whether in some cases the idea of ethical investment is a marketing catch-phrase rather than a seriously meant commitment. This illustrates that there are several dimensions when it comes to setting up a basic framework of RI.

With the scope on responsibility, there is a distinction to be made between the concepts of RI and Corporate Social Responsibility (CSR). The latter is generally attributed to the field of business ethics. RI clearly focuses on investing responsibly, which may include considering CSR of investees.

As with the absence of standardization for the basic concept of RI, there is no consensus neither in academia nor in the industry on the definition of ESG. There are, however, efforts among industry

participants towards a standardization of ESG criteria. For instance, there is an extensive catalog published by the European Federation of Financial Analysts Societies (EFFAS) that specifies so called *key performance indicators* being measurable quantities within an ESG framework (EFFAS, 2010). UNPRI (2016) emphasizes that a list of ESG items is not desirable due to the dynamic nature of what ESG requirements to any participant are. The UN corporation for responsible investment (UNPRI, 2016) defines that environmental issues are related to the quality of the natural environment and natural systems in general, e.g. energy efficiency or climate change. Furthermore, social issues are related to the rights, well-being and interests of people as well as communities, e.g. human rights or workplace health and safety. Finally, governance issues relate to the governance of companies and other investee entities, covering for example board structure, business ethics or bribery and corruption issues. Despite a potential agreement on broad definitions like the named, there are obvious reasons why it is difficult to find consensus on what ESG is about. ESG conceptions differ not only from sector to sector, but are also highly dependent of the stakeholders perspective. Regulatory instances, investors, companies or NGOs are likely to differ in their notion about what ESG should incorporate.

2.2 ESG Strategies

The question of how ESG concerns are integrated into the investment process is essentially a matter of which strategy or which combination of strategies to choose. However, similarly and also related to the fuzziness of definitions in section 2.1, there is also a certain vagueness when it comes to categorization and definition of RI strategies. Some of the most influential networks, such as Eurosif, PRI, GSIA³, EFAMA⁴ distinguish five to seven strategies (s. Table D.1 in Appendix D), that are to some extend congruently defined among the organizations.

The most traditional way of aligning investments towards responsibility is **exclusion** or negative screening. This strategy was already pursued by early RI retail funds in the U.S. and the U.K (Sparkes and Cowton, 2004). It comprises the avoidance of titles or sectors that do not comply with ethical or ESG criteria as defined by the investor. From an investor's perspective, this may be motivated by

³ The Global Sustainable Investment Alliance (GSIA) is an investors based global network of sustainability oriented members (GSIA, 2015)

⁴ The European Fund and Asset Management Association (EFAMA) represents the European investment management industry (EFAMA, 2014).

risk management considerations, responsibility claims or also by religious guidelines (exclusion of so called *sin stocks*), Law and Yau (2008)). There is also a distinction to be made between a voluntarily chosen strategy of exclusion and one that is mandatory by law. An example for the latter are several countries prohibiting investments in companies linked to cluster munitions or anti-personnel landmines (Eurosif, 2014). Generally, exclusion criteria may be applied in case of human rights violation, poor labor conditions, environmental carelessness, defense, animal testing, alcohol, tobacco, gambling or pornography (Renneboog et al., 2008b) to name some prominent examples. In practice, to rule out inappropriate investments, often thresholds are defined in terms of e.g. a percentage maximum of the company's returns generated by non-compliant business activities Sparkes (2003). Once some kind of exclusionary filtering has been conducted, financial and quantitative selection is applied (Renneboog et al., 2008b). Exclusions represent by far the most widespread strategy according to the latest global GSIA (2015), European Eurosif (2014) and U.S.-based studies USSIF (2015).

Another strategy similar to exclusion is often referred to as **norms-based screening**. Sometimes, this strategy is distinguished from exclusion only sub-categorical as in De Graaf and Slager (2006). The notion is to apply a set of standards that is typically predefined by an international organization like the Organization for Economic Co-operation and Development (OECD) or the United Nations Global Impact (UNGI). Also, the orientation to guidelines set by industry initiatives and codes may be considered as norms-based screening (Scholtens, 2014). Based on these screening guidelines investors normally react upon non-compliance with their standards in first conducting deeper analysis, second either exclude the respective investment from the portfolio or engage with the according company (Eurosif, 2014).

As opposed to exclusion or norms-based screening being negative filters, there is also a **positive screening** strategy, sometimes called **best-in-class** strategy. By following positive screening, not the weak ESG performers are penalized or excluded, but the stronger ones are rewarded or included. Consequently, this also may evoke an incentive for companies to increase ESG efforts. In practice typically only some defined top percentile with respect to ESG criteria within a sector is considered in the portfolio selection. As defined by Eurosif (2014), not only the investable universe may be narrowed down this way, but also the relative allocation within portfolio construction may depend

on ESG-factors besides financial input criteria. Best-in-class approaches can be mainly criticized in two ways: (i) it is questionable to what extent a conscious investor's needs are met when the best few ESG scoring companies out of a sector with on average poor ESG performance are included, (ii) RI-fund holdings and non-RI-fund holdings are found to be markedly similar, which is mainly due to the barely exclusive investment style facilitated through best-in-class methods (Schröder and Nitsche (2015), Midttun and Joly (2010)).

A further strategy is categorized as **sustainability themed** or **ESG themed investments**. Typically, single issues in the field of RI like climate change, cleantech or energy efficiency are addressed through the selection of according investments (Eurosif, 2014). There are funds following this strategy that focus on single or multiple ESG subjects (clusters) thematically (Scholtens, 2014). UNPRI (2012) detects different motives to implement this strategy; to effectuate an environmental and social impact, to achieve enhanced risk-return profiles as well as to improve the degree of diversification and to participate in growth. The same publication mentions that sustainability themed investments are underrepresented in an average portfolio as there exist several barriers. Among others, the lack of historical track record data and high levels of perceived risk are mentioned, since these investment areas are often considered as immature.

ESG integration as defined in Eurosif (2014) and UNPRI (2016a) is the explicit incorporation of ESG risks and opportunities in traditional financial analysis. Generally, integration encompasses the use of qualitative as well as quantitative ESG information in the investment process and aims at enhanced investment decision making (UNPRI, 2016a). The methods covered in Chapter 3 as well as the proposed framework in Chapter 4 can be attributed to this strategy. Eurosif (2014) splits integration into two categories: (i) *non systematic ESG integration* being described as ESG analysis and research made available to analysts and fund managers; (ii) *systematic ESG integration* embraces systematic consideration and inclusion of ESG research or analysis of financial ESG factors. Also, financial ratings or valuations that are derived from ESG analysis and that lead to mandatory investment constraints (e.g. weighting schemes or exclusions) are considered as ESG integration. Still, this narrower definition is matched by most of the methods in scope. Integration may be used on either the portfolio level, the stock, issuer or investee level (UNPRI, 2016a). The integration strategy is applied increasingly by institutional investors who commit to RI but at the same time

try to avoid to be exposed to the potential restrictions to the investable universe caused by several screening methods (Staub-Bisang, 2015). Yet, integration as defined above still embraces a wide spectrum of implementations. According to Fung et al. (2010) the practices reach from a combination of other strategies matching the technique to the type of portfolio, asset class or mandate, to the inclusion of ESG metrics as additional input data to quantitative financial models. The difference to other strategies may seem marginal, as for example best-in-class approaches may as well incorporate ESG factors systematically. The emphasis lies, however, on the integration in traditional financial analysis, i.e. the consideration of ESG criteria besides risk and return in the analysis of securities or companies (Friesenbichler, 2016). Herein also lies one of the potential barriers for asset managers to implement integration: risk and return are objectively measurable criteria, whereas ESG scores are challenged in terms of comparability and transparency (Nielsen and Noergaard, 2011). In spite of such barriers, numerous recent publications (e.g. Eurosif (2014), USSIF (2015), KPMG (2015)) consider integration as the fastest growing strategy.

Experiencing strong growth as well, the strategy of **engagement and voting** is part of the core strategies as defined in a practitioners environment. The notion here is that by means of *shareholder stewardship*, asset owners or institutional investors as their agents exercise their voting rights or engage in dialogue with companies under the premise of RI. Investors intend to influence their investees either directly or grouped in investment associations (Gifford, 2012). There are different sources of shareholder power; besides formal shareholder rights, there may also be legal proceedings to enforce shareholder rights, lobbying, investment or divestment as incentivizing or disciplining measures or placing public or private statements to affect a companies or a representative's reputation (Gifford, 2012). Given that institutional investors potentially partake in numerous companies, voting preparation may be costly, hence guidelines given by proxy advisors play a role. Also, investor networks as the UNPRI or EFAMA encourage their members in stating principles or guidelines, according to which ownership responsibilities shall be exercised and also documented for the public (e.g. EFAMA (2011)).

A strategy similar to *sustainability themed* investing is known as **impact investing** or community investing. Generally, the social or environmental component is emphasized in this strategy, yet financial return is not neglected. Rather it is a combination of philanthropic goals or at least some

focus on non-financial impacts and traditional return on investment considerations (Höchstädter and Scheck, 2015). Eurosif (2014) classifies the strategy into two broad categories; (i) social integration that aims at e.g. affordable housing, health, finance or similar fields and (ii) investment in mostly developing markets in e.g. renewable energy or sustainable agriculture. The difference between *impact investing* and *sustainability themed investing* originates mainly from the investors' motives. UNPRI (2012) distinguishes *impact first* investors from *financial first* investors. Impact investing covers a wide range of expected financial return; the goals may reach from capital preservation to a market rate of return (Wilson, 2014).

Besides the issue of ESG strategy definitions, there also remains the question what the frequently mentioned *investment process* could actually look like and which strategies may be addressed at the different steps of such a process. In Louche (2004) an insightful investment process in an algorithmic form is given. It refers to the process of an actual investment fund applying different strategies in a multiple phase model. Since an investment process is usually a matter of the fund management board defining it, there is however no universally valid design of such a process. Figure 2.1 depicts a generic investment process and assigns core ESG strategies to the different steps.

Investment Process and ESG Strategies

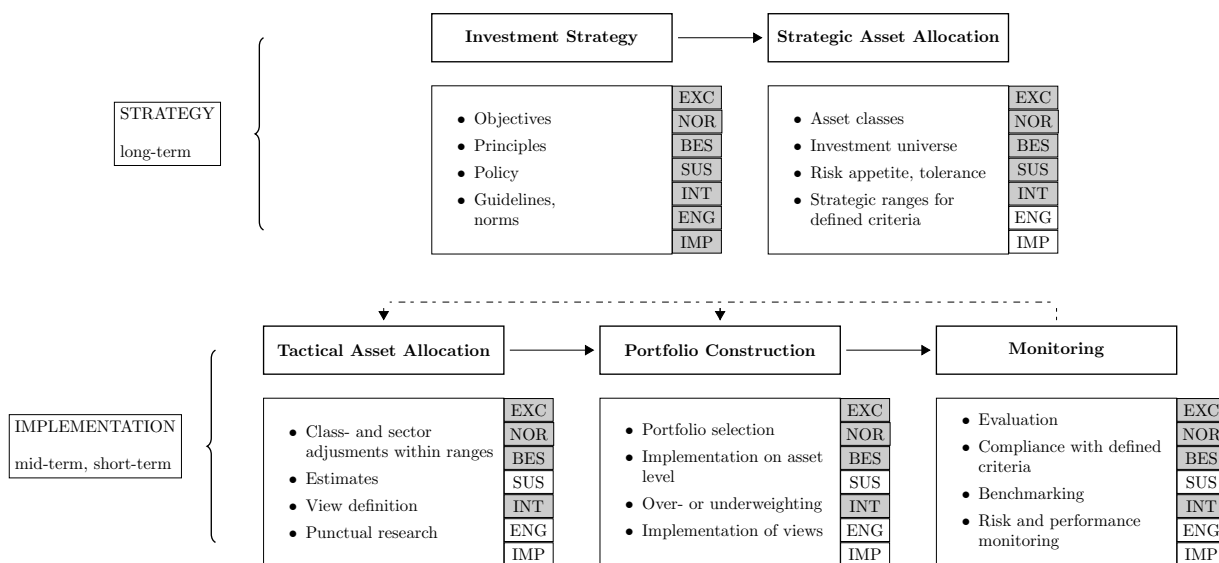


Figure 2.1 – Investment Process and ESG Strategies

This figure shows a generic investment process in an institutional investor context. The arrows imply a chronological order, i.e. the process may also be recursive after evaluation. The three-letter-boxes indicate in what stage the strategies are likely to be addressed (shaded) or not (transparent). The key to the letters is *EXC* for exclusion, *NOR* for norms-based-screening, *BES* for best-in-class, *SUS* for sustainability themed, *INT* for integration, *ENG* for engagement and *IMP* for impact investing. (Source: own figure partially based on De Graaf and Slager (2006) and MSCI (2011))

2.3 Market for Responsible Investments

The market for RI has become the fastest growing financial market segment in recent years (e.g. Fung et al. (2010)). Yet, an estimate of the total global market volume and its progression over time is challenging, since mainly above mentioned networks as the UNPRI, Eurosif or the GSIA only report in reference to their signatories. A professional investment manager may be member of different networks which vitiates the sheer addition of reported numbers over all networks. However, global network reports may reflect the market development quite well. In a global RI market study conducted by the GSIA⁵ Around 30% of total managed assets are reported to be RI assets by 2014.⁶ This corresponds to aggregated 21.3 trillion US dollars of assets under management (AUM) invested in RI, adjusted for double counting of strategies. Geographically, global RI assets are mostly European (63%) or from the USA (30%), the residual is attributed in descending order to Canada, Australia/New Zealand and Asia. The same publication identifies significant growth rates from 2012 to 2014 for the whole global market (61%), which origins mostly in the US market (76%) and least in the Asian market (0.8%). Strategy-wise the majority of assets is attributed to exclusion, followed by integration, engagement, norms-based screening, best-in-class, sustainability-themed and impact investing (see also Section 2.2).⁷ Strategy growth rates are highest for sustainability themed investing (136%) followed by ESG integration (117%), the only negative growth rate is recorded for positive screening / best-in-class (-1%). The reported growth rates in GSIA (2015) are partially caused by changes in definitions. In terms of asset classes around half of the global volume is covered by equities, followed by bonds (40%) and real estate (5%); the remaining shares go to commodities, venture capital, hedge funds and others. The demand side globally can be segmented in roughly 90% institutional and 10% private investors; this proportion seems to remain stable during the last years (GSIA, 2015).

A similar market characterization is given according to UNPRI reports. Here, by April 2016 a total of 62 trillion USD assets under management is reported UNPRI (2016b). This corresponds to

⁵ The GSIA is an association of five large RI networks; the European Sustainable Investment Forum (Eurosif), the Responsible Investment Association Australasia (RIAA), the UK Sustainable Investment & Finance Association (UKSIF) and the US Forum for Sustainable and Responsible Investment (USSIF).

⁶ The figures in this paragraph correspond to the ones reported in GSIA (2015).

⁷ Yet this ranking depends largely on the defined categorization. With for example *integration* defined in a narrower way as done in Eurosif (2014), it would not rank as second most applied strategy.

a tenfold increase since the first reporting in 2006 (see. Figure 2.2). By 2015 the dominant region in terms of UNPRI participation is Europe (53%), followed by North-America (26%) and Oceania (11%), the remaining global regions account for less than 5% each.

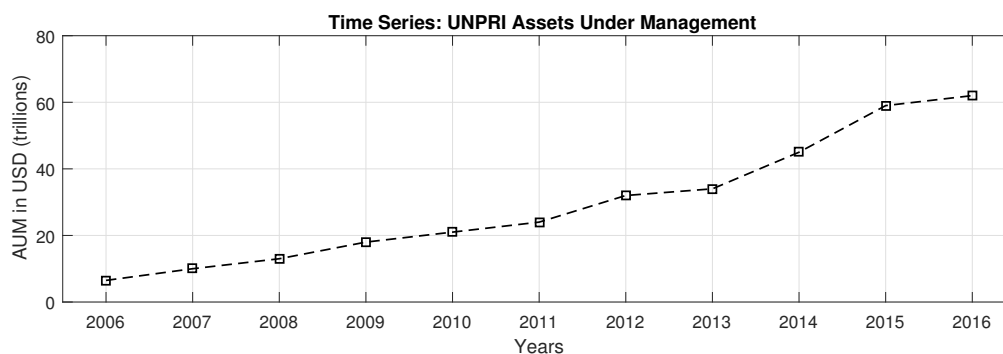


Figure 2.2 – Assets Under Management UNPRI

This plot shows a time series of yearly data of global assets under management as reported by the UNPRI network, measured by April of the corresponding year. The latest value stems from April 2016 and amounts to 62 trillion USD assets under management; these were managed by 1500 signatories. (Source: UNPRI (2016b))

Bearing most volume in a global comparison, the European RI market in aggregate is still growing at a faster rate than the broad asset management market (Eurosif, 2014). In terms of the most important asset classes and their representation in the RI market, the European proportions with around 50% equities and 40% bonds match the worldwide distribution (Eurosif, 2014; GSIA, 2015). Concerning the frequency of strategies, the predominance of exclusion approaches is also observed in Europe, followed by ESG integration⁸ and norms-based-screening.

Clearly, across all networks the reported growth rates of the market are remarkably high. This raises the question about the source of the significant market expansion after RI has lived in the shadow for decades. An obvious condition for the market to grow is the awareness within the investment community and governments of issues like climate change, energy efficiency or scarcity of natural resources. The recognition of the financial materiality of these issues undoubtedly catalyzes market growth as well (Sikken (2011), Renneboog et al. (2008b)). The raise of demand can be observed for both, large investors as well as retail funds. For the group of large investors such as

⁸ Here, ESG integration refers to the broad definition which also includes non-systematic ESG integration as the simple access for analysts to ESG research.

pension funds the typical motives to engage in RI embrace the improvement of risk-adjusted returns, signaling social responsibility and contribution to safeguard the integrity of financial markets (Sikken, 2011). It is also plausible that large investors act inline with the *universal owner hypothesis* (Hawley and Williams, 2000). The latter states that an investor who owns considerable holdings in companies and is sufficiently diversified, owns a substantial share of the whole market as opposed to a few single companies. Thus, this investor is potentially exposed to the course of the whole economy and has therefore an immanent incentive to reduce negative externalities like pollution or energy inefficiency caused by single sectors or companies affecting the whole economy. Furthermore, the rise and expansion of networks like the UNPRI or Eurosif foster the involvement of mainly institutional investors in RI (Sikken (2011), Eurosif (2014)). An important role is also attributed to regulation in single countries with respect to transparent reporting standards regarding ESG disclosure by pension funds and listed companies (e.g. Freshfields Bruckhaus Deringer (2005)). Yet, the regulatory or legislative spectrum of influence is not limited to reporting standards. For example, Swedish Pension funds are obliged to incorporate ethical and environmental issues in their investment policies since 2002 and the Netherlands grant tax deduction for green investments (Renneboog et al., 2008b). According to Eurosif (2014), also external pressure (Non-Governmental Organisations (NGOs), media, trade unions) and demand from retail investors is mentioned as important drivers of RI demand. The retail sector is considered as least important factor, although in principle, there reportedly is a potential demand from private investors (Eurosif, 2014). The reluctant participation of private investors in the RI market could be partially founded in the intermediary function of financial advisors that play an important, yet little investigated role in the financial industry. Paetzold et al. (2015) illuminate the conceptions and motives from both, the investor's as well as the advisor's perspectives and hint at potential starting-points to overcome existing barriers. According to Eurosif (2014) NGOs may influence market participants on various levels taking on different roles. Be it as provider of advocacy toward institutional investors and large pension funds, as consultants for RI funds, or even as company shareholders or as sponsors of funds (Guay et al., 2004). Furthermore, market growth of the RI sector was accelerated by the financial crisis in 2008 (Sikken (2011), Woods and Urwin (2012)); conceptually, the awareness of the financial materiality of ESG factors seems to have gained ground during the aftermath of the crisis. One reason for this indication of rethinking basic investment prin-

ciples may be found in empirical evidence of RI funds exhibiting a dampened downside risk during crises (Nofsinger and Varma, 2014).

The near future of the RI market will be determined most likely by self-imposed corporate policies as well as external impulses from forthcoming governmental regulation changes. The latter are predominantly to be expected in the area of corporate ESG disclosure. The growth of visibility of RI concepts for a wider range of investors, the growing interest in RI and the raise of ESG disclosure standards in so far underrepresented regions as the Asian market are also considered as potentially driving forces behind further global RI market growth GSIA (2015).

2.4 ESG Ratings

Credit ratings in bond markets represent organizational efficiency of the market when facing costly and complex screening activities to overcome information asymmetry problems in debt financing. A similar setup in the context of RI led to the establishment of ESG scores or ESG ratings in recent years. The heterogeneity of definitions for elementary RI or ESG concepts described above is mirrored in the plurality of the rating suppliers' methodologies (Sadowski et al., 2010; Windolph, 2013). ESG ratings differ in various ways: Keller (2015) names differences in the structure of the issuer (e.g. NGOs, index providers), source and properties of input data, weightings of ESG components, the type of rating output, rating methodology, geographic focus and intended use. Unlike credit ratings that feature to a certain degree traceable and prevalent factors focused on the debtor's probability of default, ESG ratings exhibit a broader margin of discretion. This wide range of interpretations and methodologies raises the issue of transparency, reliability and credibility of ESG ratings (Windolph, 2013). However, the existence of reliable instruments for the assessment of a company with respect to ESG considerations is pivotal for both, investors and companies. For investors, to screen firms in their portfolio or potential entries regarding the compatibility with their investment policies. For companies as an opportunity to signal ESG compliance or activities in order to attract capital more easily by passing investor screenings and being included in corresponding indices (Delmas et al., 2013). The credit rating process is claimed to be prone to biases towards rating inflation due to an *issuer-pay* based practice, where the assessed company pays the rating

provider (Partnoy, 2009; Xia and Strobl, 2012). Yet, the prevailing business model for the ESG rating practice is reported to be prevalently *subscriber-pay* based, where investors and consumers fund the ratings. Still, a conflict of interest cannot be ruled out in this market neither, since often the providers of ratings also consult the companies being evaluated (Sadowski et al., 2011). Another issue besides information asymmetries is addressed by the question of how well ESG ratings actually measure the ESG condition of a company. Chatterji et al. (2009) report some discouraging results according to which data is not evaluated optimally by certain suppliers. However, the study finds the analyzed ratings to statistically significantly predict post rating occurrence of negative governmental and environmental externalities. Wood (2010) reviews literature on the measurement of corporate social performance (CSP) and related concepts and emphasizes that CSP measurement is a function of available data, thus depending on corporate transparency in this matter. Furthermore, it is often criticized that ESG ratings or scores are to a large extent of a subjective nature. This argument is partially challenged by Keller (2015) who analyzes ESG rating procedures of single suppliers and finds the integration of quantitative data and the application of specific methods of measurement to be instruments that allow for a certain degree of objectivity.

Given that ESG scores or similar concepts are applied as integral parts of a quantitative portfolio optimization process as it is suggested in this thesis, there are several issues that require diligent inspection. As such measures represent highly condensed information being in most cases the result of some sort of data collection, weighting scheme and computational processes, it is crucial to know the ingredients.⁹ Escrig-Olmedo et al. (2014) identify a number of issues associated with the construction of sustainability indices: the choice of domains and variables, the incorporation of multi-year data, the construction of a scoring system, the selection of statistical aggregation and weighting methods. To what degree a company's ESG performance is represented by a score is thus highly contingent on the chosen parameters, methods and applied models.

Another concern when including ESG scores in investment decisions is about the causal relation between ESG measures and financial performance. When conducting empirical analysis of a hypothesized correlation between the two variables, controlling for confounding variables might be insightful. In a study published by Artiach et al. (2010), significant positive correlations between

⁹ For a description of the ESG scores used in this Master's Thesis s. Section 5.1.

corporate social performance (csp), firm size and growth capacity were found. The authors reason that the social impact of large companies is likely to be too substantial for the firms to pursue a passive policy in terms of ESG concerns. Additionally, economies of scale in implementing sustainable principles as well as regulatory pressure may explain the results. Also, companies characterized by high growth benefit from the opportunity to include ESG consideration right from the beginning into their expanding businesses. Relating these findings to the inclusion of ESG scores into investment decisions, it is (i) important to be aware that doing so may to a certain extent be equivalent to incorporating other factors that are correlated with ESG measures; (ii) firm size might be one of the most prominent confounding variables that potentially affect financial performance (e.g. Van Beurden and Gössling (2008); Artiach et al. (2010)). Furthermore, as found by Galema et al. (2008) there is also statistical evidence of high ESG-values correlating with lower book-to-market ratios.¹⁰ For an interpretation of these findings in a Fama-French model context and potential implications to an high ESG-score portfolio see Section 2.5. As further potentially confounding variables that link corporate social performance to corporate financial performance, Van Beurden and Gössling (2008) identify *industry*, *R&D expenditures* and *risk*¹¹ in a literature review study. Quite plausibly, the significance of an industry variable reflects that industries differ in coping with sustainability in terms of standards, regulation or best practices. Again, from a portfolio optimization point of view, this could result in an overrepresentation of certain industries, which potentially affects the degree of diversification. In terms of risk, high CSR level firms exhibit lower risk, which is compatible with the findings from above with respect to firm size and book-to-market ratio. According to the studies reviewed in Van Beurden and Gössling (2008) Research & Development (R&D) expenditures and CSP / CFP (Corporate Financial Performance) are interrelated as well. However, R&D factors again are related to industry affiliation as for example pointed out in Waddock and Graves (1997). Besides ESG scores being correlated to other financially relevant factors, also confounding qualities of the single components of ESG are subject of research (e.g. Manescu (2011)).

Furthermore, concerning single components of ESG ratings, the question of weighting is essential

¹⁰ This contradicts to some extent the findings of Artiach et al. (2010), who postulate a positive correlation between CSP and growth companies. In financial literature, low book-to-market ratios are associated with value stocks, as opposed to growth stocks (Fama and French, 1996).

¹¹ In most studies risk is defined as standard deviation of the stock or similar variance-based measures.

and may result in biases depending on which of the components is emphasized Windolph (2013). Often, index providers or rating agencies tend to emphasize economic criteria rather than social or environmental ones Fowler and Hope (2007). Bias issues do also appear in the selection of rated companies. As mentioned in Windolph (2013) rating providers often focus on large companies and exclude medium or small firms along with companies from emerging countries.

Moreover, condensing ESG properties of a company into a single value may be a source of potentially large trade offs in a RI context. Escrig-Olmedo et al. (2014) and Windolph (2013) point out that a sole measure might be prone to a certain offsetting effect, inasmuch as single ESG aspects of a company may be compensated reciprocally. That is, a single ESG measure is most probably not capable to meet the preference set of a RI oriented investor in detail. That said, variance, covariance or Beta (see Section 4) as a risk measurement as well cannot be able to catch all dimensions of risk in an investment context, particularly not if based on historical price movements (e.g. Engle (2004)). However, in the present thesis it is hypothesized that both measures may result in a comprehensive representation of investment relevant criteria to conscious investors, when considered in combination.

2.5 Rationale for Responsible Investments

Doing well while doing good; this formulaic phrase frequently cited in many RI-related publications may be appropriate when it comes to condense the main motive behind investing responsibly, but there are certainly more layers to rationalize RI. From religiously motivated investors through institutional ones being obliged by regulatory constraints, to the fund manager aiming to attract new assets under management, the whole spectrum of motivations is represented. Hereinafter the scope is on rationalizing RI mainly from an investor's point of view. Financially, the rationale for RI is clearly connected to the performance of responsible investments in terms of risk adjusted returns and potential correlations of a non financial with financial performance. From an economic point of view, the question of how RI may be reflected in a financial-/ non-financial utility and preference context might be of particular interest.

As pointed out in Section 1.3, there is an extensive body of literature addressing the relation

between Non-Financial Performance (NFP) or ESG performance with financial performance, or likewise corporate social performance with overall business performance. Yet, the sheer number of studies indicates a lack of consensus on that matter, such that it is reasonable to state that research is inconclusive in this regard. However, if generally considering ESG factors in the investment process is hypothesized to matter for financial performance, some of the neo-classical assumptions have to be relaxed, i.e. the focus is not only on systematic risk, markets are not considered to be fully efficient, information may be incomplete and risk may not be fully diversified (Dumas et al., 2015).

The interrelation between financial and non-financial performance may basically be divided in three scenarios from a financial theory perspective as pointed out by Manescu (2011): (i) In the *no effect scenario* there is no observable difference adjusted for common risk factors between returns generated by high ESG firms as opposed to low ESG score companies. That is, the information about ESG properties of a specific firm is already priced in and systematic excess returns above market average on the basis of this information are not possible. This scenario would be in line with the Efficient Market Hypothesis (EMH) (e.g. Fama (1998)). (ii) In the *mispicing scenario* ESG attributes of a firm are indeed value relevant, but the information is not sufficiently reflected in asset prices. This results in either higher or lower risk adjusted returns depending on the relation of costs and benefits attributed to the ESG efforts. Incomplete information effectuates over- or undervaluation contingent on the market's perception of the mentioned cost/benefit relation. (iii) The *risk factor scenario* hypothesizes low ESG score returns to be systematically higher in terms of a risk premium compensating for bearing non-sustainability risk. The risk factor scenario is also supported by the findings from Artiach et al. (2010), Van Beurden and Gössling (2008) as well as Galema et al. (2008) referred to in Section 2.4 about the effect of size and book-to-market ratios of a company to risk and return. According to these findings, on average, companies scoring high on an ESG scale tend to be big companies with low book to market values. Assuming this holds true, from a Fama-French perspective, this is equivalent to state that a portfolio being tilt to high ESG scores as compared to one with low ESG scores is on average less exposed to the risk factors inherent to small companies and growth companies, i.e. exhibits lower expected returns.¹² Section 3.1 discusses the relation between risk and ESG criteria more thoroughly.

¹² For a short recapitulation of the Fama-French three factor model see section Appendix A.1.

A recent second order meta study about the relation between ESG scores and corporate financial performance (CFP) is given in Friede et al. (2015). The study evaluates the findings of roughly 2200 studies on the individual stock as well as on the portfolio level and claims about 90% of all studies to find a non-negative relation, of which 48% (vote-count studies) or 63% (econometric meta analysis) yield positive findings in terms of ESG-CFP correlation.¹³ In the study, the importance of distinguishing between portfolio and non-portfolio studies is emphasized. Referring to this, portfolio studies exhibit significantly less positive results than non-portfolio studies. This result is also found by other studies, as e.g. Fulton et al. (2012). Friede et al. (2015) hypothesize this finding to be potentially one of the main reasons why institutional and private investors typically perceive at best a neutral ESG-CFP relation. Also, the weak effect in a portfolio context might be partially explained by MPT, since idiosyncratic risk as ESG risk is assumed to be diminished if the number of titles in the portfolio is sufficiently large by the principle of diversification. Furthermore overlapping market and non-market factors, the distortion of any remaining effects by exclusionary screen portfolios as well as the consideration of management fees or other costs may cause the observation of the weak ESG-CFP correlation of portfolio related studies (Friede et al., 2015). Similar to Friede et al. (2015) there are various other meta studies finding a positive link between ESG/CSP and financial performance (e.g. Orlitzky et al. (2003); Wood (2010); Margolis et al. (2007); Margolis et al. (2009); Clark et al. (2015), Allouche and Laroche (2005); Fulton et al. (2012)). Yet, there are also studies finding no statistically significant difference (Hamilton et al., 1993) or even negative relations, as in Renneboog et al. (2008a).

There are several issues to consider when reasoning about the relation between CSP and CFP. For instance, the causation pathway of CSP and CFP is not clear at all (Wood, 2010). There may also be confounding variables in the background that influence the superficially concluded correlation substantially. Also, the predominantly reported positive relation may be biased due to a truncated pool of published studies and as a consequence be overestimated (Rost and Ehrmann, 2015). Besides that, data as reported by companies on CSP may be prone to deception or manipulation (Woods and Urwin, 2012). Whether research claims ESG to have a positive, negative or no financial impact

¹³ Vote-count studies evaluate studies counting positive, negative and neutral findings and vote the most prevalent category as winner. Meta studies are econometrically conducted analysis of existing studies.

depends largely on the data and methods used. However, the issue whether RI is legitimated from a financial performance point of view may have been overemphasized in the literature of the last years. Capelle-Blancard and Monjon (2012) see the reason for this tilt towards financial performance in the data-driven nature of research. They confirm the importance of monetary motives to include in RI decision making but also mention altruism, reputation or self-esteem to be important motives for people to be responsible investors. In fact, there is evidence that the latter are willing to forego financial return to a certain degree for the benefit of achieving their non-financial goals; Benson and Humphrey (2008) as well as Renneboog et al. (2011) find RI fund flows to be less sensitive to past returns as compared to conventional funds. This has its origins in non-financial returns for specific investors and shareholder stewardship, but also in minimizing risk.

When rationalizing RI, financial return is doubtlessly important, yet no less are market beliefs, being a major determinant of money flows. In a study focusing on the Swedish market, investment motives for institutional and private responsible investors were explored. It was found that particularly institutional investors believe that investments in RI assets are rewarded with higher returns in the long run and reduced risk, i.e. exhibit better risk-adjusted return than conventional investments (Jansson and Biel, 2011). With a focus on institutional investors, Freshfields Bruckhaus Deringer (2005) attach belief based conditions to engage in ESG investing. Thereafter ESG considerations must be taken into account if such considerations are reasonably believed to be consensual amongst beneficiaries, or to have a material impact on the financial performance of that investment. Moreover, if ESG consideration provides a point of differentiation within a set of equally attractive alternatives, the consideration may be taken into account.

Hence, to base the justification of RI solely on potentially advantageous risk-return characteristics would fall too short. *Ipsa facto*, non-financial incentives in the form of personal motives or institutional sustainability goals towards the contribution to the environmental, social and governmental prosperity of the economy are essential. RI may provide appropriate measures to promote change in a shareholder based economy, for example in financing the transition to renewable energy (Kerste et al., 2011). It is also plausible to think of ESG investing having a disciplining effect on companies, which particularly might hold true if investors in terms of the above mentioned universal owner theory gain influence and engage directly with their investees. Furthermore, ESG considerations may

enhance security selection as well as risk management processes CFA (2008). ESG performance can also be seen as a proxy for management quality, representing a company's ability to respond to long term trends Bassen and Kovacs (2008).

On a conceptual economic theory level, RI may be rationalized through social preferences, which for example are defined in Fehr and Fischbacher (2002) as caring not only about material resources allocated to oneself, but also to relevant reference agents. Starr (2008) connects pro-social behavior found in social preference experiments to be reflected in RI. In particular, fairness related sanctioning is referred to, inasmuch as companies are screened in or out of a portfolio, depending on whether they treat their shareholders in a *fair* way. In terms of utility theory RI may also be legitimated against the background of the Prospect Theory, as stated by Kahneman and Tversky (1979). The specific value function of this seminal behavioral finance paradigm reflects empirically substantiated loss aversion. Assuming a mitigated downside risk related to RI assets, ESG consideration in investment decisions may provide value for investors that may be described by the Prospect Theory value function.

Quantitative Integration of ESG measures into Portfolio Construction

The following sections are about systematic integration of ESG criteria in the investment process as described above and in Eurosif (2014) and also USSIF (2015). The scope is even further narrowed down in two ways: the first requirement to qualify as a relevant method in the sense of the present thesis is the quantitative integration into portfolio construction and portfolio management in particular. Second, as opposed to the widely spread and often mentioned two-step-approach, where in the first stage some exclusionary filter is applied to then financially optimize the portfolio traditionally in the second stage, the ESG inclusion is required to be done simultaneously, or integrally. Approaches that meet these requirements are named Integral Quantitative Integration of ESG-criteria (IQIE) and represent quantitative integration of ESG criteria in the narrowest, purest sense. Yet, the simultaneity requirement may be temporarily relaxed, such that approaches featuring a sequential implementation are taken into account as well for the sake of comprehensiveness. However, there is by no means any claim to completeness in the review of approaches. A rationalization of IQIE approaches that goes beyond the general reasoning for RI (Section 2.5) as well as possible impediments are given in this chapter. It then provides basic theoretical frameworks being a preliminary part to discuss a selection of existing IQIE approaches in the narrow and the as well as the wider sense. The description of the different approaches aims at reviewing the methods beyond the mere

restatement of the according abstracts. Therefore it contains methodological details that contribute to the understanding of the applied principles.

3.1 Rationale and Impediments for Quantitative Integration

As insinuated in the above sections, standard MV text book portfolio optimization methods concentrating solely on the maximization of future financial returns may fall short generally (Steuer et al., 2007), and if one allows for investors aiming to act responsibly more specifically (Hallerbach et al., 2004). As underlined in Renneboog et al. (2008b) or Bollen (2007) the existence of multi-attribute utility function investors, that consume the *social responsibility attribute* of an investment is beyond controversy. Some investors seem to prefer a mixture of RI and conventional funds, and the optimal mixture could be determined by multi-attribute portfolio maximization (Hallerbach et al., 2004; Lewis and Mackenzie, 2000; Von Wallis and Klein, 2015). Indeed, pension funds as the most represented group of investors in an RI context (see Section 2.3) already account for ESG factors. Notwithstanding most of them typically apply a specific form of exclusionary screening in the first place, to then allocate the fund's wealth to the selected assets in a financial optimization in the second phase (Hirschberger et al., 2012; Nielsen and Noergaard, 2011). This procedure is not considered IQIE method, since negative screening is merely the - more or less - sophisticated exclusion of assets according to predefined filtering. Thus, despite the fact that systematic integration is gaining grounds for the last years, there still seem to be impediments as to integrating ESG measures quantitatively. The main reason for the predominance of the MV paradigm and the minor importance of ESG consideration in an institutional investors context is based on the historical concentration of the finance industry on Modern Portfolio Theory (MPT) and variations thereof (Brandstetter and Lehner, 2015; Richardson, 2011; Wood et al., 2012, 2013). Also, Juravle and Lewis (2008) find the notion of *fiduciary duty* to be one of the main contra-arguments for institutional investors. According to common law jurisdictions¹⁴ the duty to act in the best interest of the beneficiaries is fulfilled by pursuing the modern portfolio approach in investment decision making, thus to maintain an optimally diversified portfolio (Freshfields Bruckhaus Deringer, 2005; Juravle and Lewis, 2008).

¹⁴ For UK, US and similarly for Germany and France.

If MPT is applied in its strictest form, then any restriction to the asset universe produces inferior portfolios from a MV point of view. It seems to be a potential source of uncertainty for institutional investors that depends on whether ESG consideration constitutes or is perceived a breach of fiduciary duty. Yet, as reported in Freshfields Bruckhaus Deringer (2005), there is no jurisdiction to prescribe how to integrate ESG considerations into investment decision making. Richardson (2011) finds legal and practical issues, such as how the *beneficiaries' best interest* should be defined, when there is no unanimity on investment principles among them. Sikken (2011) identifies restrictions in conventional valuation models as one of the key barriers for ESG investments, and non-financial indicators may not be accounted for as a result of prevailing mindsets of investors. Related to this, according to Brandstetter and Lehner (2015), the commitment of pension funds to class specific benchmarks for expected financial risk and return can be seen as an impediment for the inclusion of ESG criteria, besides the adherence to conservative legal and policy-related requirements. Also, ESG inclusion causes additional cost, especially if ESG research is done in-house, which adds an expenditure-revenue dimension to the problem. In a series of interviews with professionals, Nielsen and Noergaard (2011) identify also the lack of material proof that RI funds outperform conventional ones, time constraints, asset managers' limited expertise in ESG matters and the lack of standardized data as barriers to the more sophisticated integration of ESG into portfolio management.

To overcome most of the mentioned key barriers, there is a need for more conceptual and theoretical work on the quantification of ESG and the inclusion of such a measure into portfolio selection (Capelle-Blancard and Monjon, 2012; Nielsen and Noergaard, 2011; Von Wallis and Klein, 2015). The rationalization of IQIE approaches is essentially founded in the notion of covering risk dimensions other than short term market risk. ESG covers risks that potentially influence the earning power, reputation and the balance sheet profoundly (Aeby, 2014). Well known recent examples for incidents related to poor ESG properties harming involved companies are BP, Tokyo Electric Power Company, Foxconn, Siemens, Lonmin or Barclays (Aeby, 2014; UNPRI, 2016b). Kiernan (2007) suggests that recent company implosions have revealed the weak spots of conventional financial assessment of investees and propelled the urgency of considering alternative measures related to ESG issues. There is evidence that indeed ESG metrics capture risk that is not assessed by traditional fundamental risk forecasts. UNPRI (2016a) concludes that poor ESG ratings can help reveal companies with

high future volatility. Hoepner (2013) links a portfolio of high ESG score titles empirically to lower overall downside risk or dampened worst case outcomes respectively. Quigley (2009) reports the bottom quintile of ESG companies to exhibit a forecasted risk typically considerably higher than for top quintile stocks. In a semi-deviation based analysis Dumas et al. (2015) find evidence for ESG metrics to have a limiting effect to downside volatility. Related to such findings of RI and mitigated risk is the evidence of high ESG scores being correlated with lower cost of debt (Attig et al., 2013; Bauer and Hann, 2010; Cheng et al., 2014). It is also emphasized in Freshfields Bruckhaus Deringer (2005), that the long term risk and performance dimension may be incorporated by taking ESG into account with respect to embracing fiduciary duty more appropriately. Thus, considering the relation between risk and ESG, the variance input of MPT models might capture only parts of the full risk spectrum, which is why ESG considerations, where appropriate, should be included in the most accurate way possible.

Related to risk considerations, the concern about inferior diversification effects (Sparkes, 2003) caused by exclusionary screening may be tackled through including ESG criteria in portfolio construction. Depending on the applied constraints, a sophisticated portfolio construction method facilitates the consideration of ESG measures on a continuous scale rather than being bound to the binary decision when applying some exclusionary screening. An example for a method taking into account such reasoning is given in the proposed method in Chapter 4. Also there are other examples for portfolio weight shifting on the basis of ESG measures applied by actual funds as described in UN-PRI (2016a); Nagy et al. (2013) elaborate weight shifting methods as well find portfolio performance raised after underweighting low ESG scored assets.

The MPT belongs without any doubt to one of the most influential concepts of finance theory and it is widely adopted in some form by institutional investors for comprehensible reasons. However, the theory has been challenged in academia multifariously. The sole focus on stock prices and the volatility thereof may be a too myopic set of inputs when shaping investment vehicles. Asset prices are increasingly short term driven (e.g. by quarterly statements), i.e. stock prices lose the capability to reflect long term estimates, objectives or strategies (Rappaport, 2005). That is, focusing on MV criteria solely, which is a property of MPT approaches, potentially excludes this dimension to some extent. This effect could be mitigated by incorporating ESG criteria systematically. More generally,

Nielsen and Noergaard (2011) claim that integrated models (as opposed to dual decision, sequential models) considering ESG as well as financial criteria are able to capture the value generated by beneficial CSR properties of investees. Further it is left open in Nielsen and Noergaard (2011), how such IQIE-models could look like. Yet in interviews with analysts and investors it was found that they are willing to use more sophisticated methods that include ESG data.

A further reason to consider IQIE approaches is the ability to respond to changes in ESG scores promptly in rebalancing the portfolio accordingly. As found in Wimmer (2012), ESG scores for funds are on average persistent for approximately two years before they typically decrease. Yet, it is found in the same study, that drops in ESG ratings were caused by RI fund managers' changes to their portfolios, not by decreasing ESG scores of the initial assets in the portfolios. Wimmer (2012) concludes that this is due to the typical pattern found in RI funds of ESG screening in the first stage and then performing strictly financial optimizing in the second stage. Once the portfolio is set up, fund managers seem to lose the focus on ESG scores. The rebalancing property of IQIE approaches is also favorable in the sense of managers being able to combine positive and negative screening in terms of over- or underweighting due to ESG scores. In practice a balanced consideration of positive and negative ESG considerations is neglected in favor of the mere use of exclusionary screens by a majority.

When advocating sustainable investment as a societal phenomenon, the rationalization for frameworks that quantitatively incorporate ESG measures lies in using instruments that most fund managers are familiar with. Also, combining traditional financial portfolio optimization techniques with ESG consideration enables fund managers to anchor large cap or large index allocations. This potentially fits the needs of ESG investors not wanting to be exposed to the niche market risk of e.g. impact investing (Quigley, 2009) or are to some extent bound by index tracking.

It seems that investors are only at the beginning of incorporating ESG more systemically and taking RI to a more sophisticated practice than exclusionary screening. Recent publications of networks like Eurosif (2014) show the emergence of IQIE approaches. In a survey USSIF (2015) conduct interviews with signatories on how ESG concerns are actually integrated in the investment process; most investors still maintain some form of ESG pre- and post-investment integration, some of them investigate how to incorporate ESG criteria into portfolio construction. There are some

approaches mentioned that include weight shifting according to ESG metrics. A promising result regarding IQIE approaches is reported in Nagy et al. (2013). A strategy named *ESG momentum* that overweights firms whose ESG ratings improved over the preceding period, results in superior risk-adjusted returns and benchmark outperformance during 2008 to 2012, there was a similar outcome for underweighting low ESG score assets. It is hypothesized that not only long term ESG effects matter, but also accounting for short term ESG downgrades that are mainly event-driven contributes to a strategies outperformance.

3.2 Underlying Theoretical Concepts

As most of the following approaches refer to Multi-Objective Optimization and the Modern Portfolio Theory, these concepts are discussed preliminarily in the following subsections, before delving into the single approaches.

3.2.1 Multi-Objective Optimization and Pareto Efficiency

Mathematically, many of the methods in scope of the present thesis are to be found in the realm of Multi-Objective Optimization (MOOP)¹⁵. The typical MOOP problem set can be described in the following generic form (e.g. Deb (2014)):

$$\begin{cases} \arg \min_x & F(\mathbf{x}) \\ \text{subject to} & \mathbf{x} \in S \end{cases} \quad (3.1)$$

where $F(\mathbf{x}) = (f_1(\mathbf{x}), f_2(\mathbf{x}), \dots, f_k(\mathbf{x}))$ is a set of objective functions, $\mathbf{x} = (x_1, \dots, x_n)$ is a vector of decision variables and S is the feasible set as defined by a set of constraints. To formalize the mapping between the n -dimensional decision variable space X and the m -dimensional objective space Z it is defined that for each solution \mathbf{x} there is a representation in the objective space that is defined as $f(\mathbf{x}) = \mathbf{z} = (z_1, z_2, \dots, z_M)$. Typically, such problems feature conflicting objective functions and require to find a set of Pareto optimal (non-dominated, efficient) solutions. In the majority of cases,

¹⁵ MOOP is a sub-discipline of Multiple Criteria Decision Analysis (MCDA), which itself belongs to the area of *Operations Research*.

there is no single solution but several efficient solutions to MOOP. Mathematically, Pareto efficiency is defined as follows (Ehrgott, 2006; Miettinen, 2012):

Definition 3.1. For a set of minimizing objective functions, a decision vector \mathbf{x}^* is said to be Pareto efficient or non-dominated if and only if there exists no $\mathbf{x} \in S$, such that $f_i(\mathbf{x}) \leq f_i(\mathbf{x}^*)$, for all $i \in \{1, \dots, n\}$ and $f_j(\mathbf{x}) < f_j(\mathbf{x}^*)$ for at least one objective function j . It is said to be *weakly* Pareto efficient if and only if there exists no $\mathbf{x} \in S$, such that $f_i(\mathbf{x}) < f_i(\mathbf{x}^*)$, for all $i \in \{1, \dots, n\}$. Equivalently, the same holds true for the objective space Z ; \mathbf{z}^* is Pareto efficient if the corresponding decision vector is Pareto efficient. \triangle

For a graphical representation of (weak) Pareto efficiency in the case of two objective functions, see Figure C.1 in Appendix C. A well known set of Pareto optimal solutions in a financial theory context is the Efficient Frontier in the plane spanned by standard deviation and expected return in the MPT framework (see Section 3.2.2). Typically, Pareto optimal solutions represent solutions that are acceptable or potentially optimal according to the specification of a decision maker; to narrow down the set of solutions further or to determine the best solution, usually additional information on preferences is needed (Coello et al., 2002). Related to this, in literature two main categories of tackling MOOP are distinguished: *A priori* methods feature the determination of the decision maker's preferences before any optimization task is performed; in *a posteriori* approaches the set of trade-off solutions is first found and then a single preferred solution is determined (Deb, 2014). There are numerous methods of finding solutions to MOOP. They may be categorized in classic methods as the *weighted sum* or the ϵ -*constraint* approach (s. also Section 3.3) to name the most popular, and on the other side the stochastic search strategies such as *evolutionary algorithms* approximating Pareto optimal solutions, where in analogy to natural evolution, solution candidates are treated as individuals and a set of solution candidates as population (Zitzler et al., 2004). Thus, Pareto efficient sets are often computed approximately. For most search algorithms therefore special vectors as starting points in the Z space are defined that facilitate the search for efficient solutions, for more details on these vectors see Appendix A.6.

3.2.2 Modern Portfolio Theory

Inter alia based on the economic principle of Pareto efficiency, Markowitz developed the MPT (Markowitz, 1991) back in 1952.¹⁶ The MPT framework is one of the key pillars of financial theory. It covers portfolio optimization with respect to expected return (mean) as the desirable part coming at the price of risk (variance). The core insight of MPT is that within a portfolio of many risky assets, it is not the risk of the single assets that matters, rather the contribution of the assets to the overall portfolio risk, giving rise to the idea of interrelated returns and diversification. By assumption a MV-investor forms beliefs about returns that are random variables, their volatility and the covariances of return movements. As the returns are not known beforehand, but the optimization has to be carried out in terms of expected values, the optimization is a stochastic programming problem. Based on those estimates, and for the time being an asset universe without a riskless asset assumed, a portfolio is chosen out of the set of all portfolios constituting the Efficient Frontier according to the investor's preferences. The Efficient Frontier is a subset of the minimum variance set, which includes all feasible portfolios for any given level of expected portfolio return and minimized portfolio variance. The latter has the form of a parabola and only the subset above the global minimum variance portfolio is considered as efficient (see Figure ?? and C.2 in the corresponding Appendices). Portfolios below are dominated, i.e. not efficient, since there is a portfolio with the same standard deviation but a higher expected return on the upper opposite of the parabola.¹⁷ The minimum variance set is defined by the following equation:

$$\begin{cases} \arg \min_w & \mathbf{w}'\Sigma \mathbf{w} \\ \text{subject to} & \mathbf{w}'\boldsymbol{\mu} = \mu_{PF} \\ & \mathbf{w}'\mathbf{1} = 1 \end{cases} \quad (3.2)$$

where \mathbf{w} is a vector of N portfolio weights in the case of N risky assets, \mathbf{w}' is \mathbf{w} transposed, Σ is the positive definite matrix of $N \times N$ covariances, $\boldsymbol{\mu}$ is a vector of N expected returns, with $E(R_i) = \mu_i$ and $R_i = \frac{Price_{i,t}}{Price_{i,t-1}}$, μ_{PF} is the expected return of the portfolio, here at a given (required) level and $\mathbf{1}$ is a vector of N ones. For the derivation of the portfolio variance see Appendix A.2. Problem 3.2

¹⁶ For an in-depth analysis consider Hens and Rieger (2010) being the main source of the following content.

¹⁷ For a visual representation of the Efficient Frontier and some explanatory remarks with respect to Pareto efficiency see Appendix A.4.

can be solved by minimizing a Lagrangian function of the form

$$\mathcal{L} = \frac{1}{2} \mathbf{w}' \Sigma \mathbf{w} + \gamma (\mu_{pf} - \mathbf{w}' \boldsymbol{\mu}) + \delta (1 - \mathbf{w}' \mathbf{1}) \quad (3.3)$$

with γ and δ as Lagrangian multipliers.¹⁸

If by assumption all assets are risky, the answer to which portfolio a MV investor should choose out of all the possibilities on the Efficient Frontier is answered by means of some utility function. In a MPT context, a rational investor's preferences are modeled based on an expected utility function satisfying axioms defined by Von Neumann and Morgenstern (1947) (s. Appendix A.5 for a definition of the axioms). For a utility function to reflect rational preferences, it has to meet the requirement of continuity, being monotonically increasing and bounded or asymptotically increasing (Hens and Rieger, 2010). Also, when utility is attributed to an uncertain monetary outcome, usually the assumption of risk aversion is made. This essentially means that a risk averse person prefers to get an amount with certainty as opposed to gambling for the same expected amount under uncertainty. It does imply that the expected value of an uncertain payoff must be at least a specific risk premium above the a certain payment for the risk averse agent to enter the lottery. For further explanations concerning concave utility functions and risk aversion see Appendix A.7. One specific functional form that is frequently used in a MPT context (e.g. Hens and Rieger (2010)) is the quadratic utility function of them generic form:

$$U_i(\mu_{PF}, \sigma_{PF}^2) = \mu_{PF} - \frac{\rho_i}{2} \sigma_{PF}^2 \quad (3.4)$$

with U_i being the utility for investor i , σ_{PF}^2 the portfolio variance and ρ_i the risk aversion parameter specific to the individual investor, quantifying the required compensation for risk with return, and the other variables as described above. Portfolio return increases utility, while portfolio variance decreases it depending on the risk aversion parameter. The latter determines where an investor's highest utility indifference curve is tangential to the Efficient Frontier, i.e. the position of the optimal portfolio for the investor in the MV space. Mathematically, the optimal portfolio for investor i is

¹⁸ For a step-by-step solution of this problem see Hens and Rieger (2010) or Zuber (2012).

found by solving

$$\begin{cases} \arg \max_w & \mathbf{w}'\boldsymbol{\mu} - \frac{\rho_i}{2}\mathbf{w}'\boldsymbol{\Sigma}\mathbf{w} \\ \text{subject to} & \mathbf{w}'\mathbf{1} = 1 \end{cases} \quad (3.5)$$

The optimization setup changes if a riskless asset is introduced, i.e. an asset without any volatility. Conceptually, an investor is now able to borrow or lend money at the riskfree rate R_f . In this environment, any combination of the tangential portfolio¹⁹ and the riskless asset lies on the Capital Allocation Line (CAL) (see Figure C.2 in Appendix C), which essentially reduces an investor's optimization problem to deciding on the proportions attributed to the risky tangential portfolio and the riskless asset according to the individual risk aversion. Mathematically, the optimal portfolio for investor i is found by solving the (unconstrained) maximization problem

$$\arg \max_w U_i(\mu_{PF}, \sigma_{PF}^2) = \arg \max_w R_f + \mathbf{w}'(\boldsymbol{\mu} - R_f\mathbf{1}) - \frac{\rho_i}{2}\mathbf{w}'\boldsymbol{\Sigma}\mathbf{w} \quad (3.6)$$

with the first order condition and optimal portfolio weights \mathbf{w}^*

$$\frac{\partial U}{\partial \mathbf{w}} = \boldsymbol{\mu} - R_f\mathbf{1} - \rho_i\boldsymbol{\Sigma}\mathbf{w} = 0 \iff \mathbf{w}^* = \frac{1}{\rho_i}\boldsymbol{\Sigma}^{-1}(\boldsymbol{\mu} - R_f\mathbf{1}), \quad (3.7)$$

where $\boldsymbol{\Sigma}^{-1}$ is the inverted covariance matrix.²⁰ Equation 3.6 shows that, except for the scaling scalar ρ_i each investor is invested in the same portfolio of risky assets, which is the basic idea of the Two Fund Separation Theorem stated by Tobin (1958). Only the proportion of the amount invested in the risky portfolio and the riskless asset differs among investors. For a graphical representation of the CAL and the separation theorem see Figure C.2 and Appendix C.

3.3 Multi-Objective Optimization Methods

There is an extensive body of literature (e.g. Ehrgott et al. (2004), Lo et al. (2003)) on the implementation of Multiple Criteria Decision Analysis (MCDA) or MOOP methods in a portfolio optimization

¹⁹ The tangential portfolio refers to the risky portfolio that maximizes the slope in the return and risk space, when a line through the riskfree asset and the risky portfolio is drawn.

²⁰ Note that the weight w_0 attributed to the riskless asset can be expressed by $w_0 = 1 - \mathbf{w}'\mathbf{1}$, where $\mathbf{w} = (w_1, w_2, \dots, w_n)$ for N risky assets. Thus, the constraint is substituted into the objective function in equation 3.6, as $\mu_{PF} = \mathbf{w}'\boldsymbol{\mu} + (1 - \mathbf{w}'\mathbf{1})R_f$.

context with a multitude of criteria additional to mean and variance, such as *liquidity*, *dividends*, *sustainability*. In this section, the focus lies on literature contribution with at least some relation to ESG.

To outline the basic principle of such methods, two of the most prominent basic approaches in the classic field of MOOP, the above mentioned *weighted sum* and the ϵ -*constraint* approach are discussed.

The *weighted sum* method consists basically of scalarizing a set of objectives by the attribution of weights to the objective functions and optimizing the weighted sum. This may be formulated as follows:

$$\begin{cases} \arg \min_x & \sum_{i=1}^k \lambda_i f_i(\mathbf{x}) \\ \text{subject to} & \mathbf{x} \in S \end{cases} \quad (3.8)$$

where S is the feasible set as defined by a set of constraints, λ_i is a set of weights, where $\sum_{i=1}^k \lambda_i = 1$ and $\lambda_i \in [0, 1]$. The weights λ_i determine the location of the weak efficient solution to Problem 3.8 on the set of efficient solutions.²¹ To compute the Pareto efficient set, Problem 3.8 is solved for different weight combinations. For a visual representation of the weighted sum approach as well as the below mentioned ϵ -constraint approach, see Figure C.3 in Appendix C. The weighted sum approach is a simple method to tackle a MOOP, yet, depending on the setup, it might not capture all solutions due to several issues, also finding Pareto optimality with this method does necessitate convexity (Deb, 2014; Ehrgott et al., 2004).

The ϵ -constraint method overcomes several of the shortcomings linked to the weighted sum approach. For instance, convexity is not a necessary condition for finding efficient solutions. Haimes et al. (1971) reformulate the generic MOOP from Problem A.10 in such a way that just one objective is retained while the other objectives are treated as constraints. The problem for the j th out of k objective functions becomes

$$\begin{cases} \arg \min_x & f_j(\mathbf{x}) \\ \text{subject to} & f_i(\mathbf{x}) \leq \epsilon_i, i = (1, \dots, k), \forall i \neq j \\ & \mathbf{x} \in S. \end{cases} \quad (3.9)$$

²¹ For a proof that the solution to Problem 3.8 is (weakly) efficient see Appendix B.1.

Problem 3.9 is solved for $j = (1, \dots, k)$ and for different values of the ϵ constraints to generate the Pareto efficient set. The success of an algorithm based on this method is highly dependent on choosing ϵ values. For a proof that the solution to Problem 3.9 is weakly efficient, and under which conditions it is strictly efficient, see Appendix B.2. In a portfolio optimization context, ϵ -constraint methods are particularly useful since the covariance function is strictly convex (see Appendix A.8 for a definition, also Evstigneev et al. (2015) for further mathematical discussion). If there is a solution to a strictly convex problem, this solution is unique and if it is unique, it is strictly efficient (see Appendix B.2 for a proof), which reduces the computational effort to generate the efficient set. For a graphical representation of the weighted sum and the ϵ -constraint approach in the case of two objective functions, see Figure C.3 in Appendix C.

Both, the weighted sum approach as well as the ϵ -constraint method are implemented by Lundström and Svensson (2014) in an ESG context based on the following problem:

$$\left\{ \begin{array}{ll} \arg \max_w & \mathbf{w}'\boldsymbol{\mu} \\ \arg \min_w & \mathbf{w}'\boldsymbol{\Sigma}\mathbf{w} \\ \arg \max_w & \mathbf{w}'\boldsymbol{\gamma} \\ \text{subject to} & \mathbf{w}'\mathbf{1} = 1 \\ & 0 \leq w_i \leq 1 \quad \forall i \in (1, \dots, N) \end{array} \right. \quad (3.10)$$

Optimization Problem 3.10 maximizes the portfolio return, while minimizing the portfolio variance and maximizing the portfolio ESG-performance, where $\boldsymbol{\gamma}$ is a vector of N expected ESG-performance values.²² The constraints for the weights summing up to unity and taking a value between 0 and 1 do not allow for short selling. To find solutions to problem 3.10, on the one hand, the following weighted sum approach is formulated:

$$\left\{ \begin{array}{ll} \arg \min_w & -\lambda_1 \mathbf{w}'\boldsymbol{\mu} + \lambda_2 \mathbf{w}'\boldsymbol{\Sigma}\mathbf{w} - \lambda_3 \mathbf{w}'\boldsymbol{\gamma} \\ \text{subject to} & \mathbf{w}'\mathbf{1} = 1 \\ & 0 \leq w_i \leq 1 \quad \forall i \in (1, \dots, N), \end{array} \right. \quad (3.11)$$

²² Lundström and Svensson (2014) construct an index value and assume it to feature Martingale properties, i.e. the expectation is equal to the last observed value.

where the λ_i with $i = (1, 2, 3)$ are non-negative weights and $\lambda_1 + \lambda_2 + \lambda_3 = 1$. For different values of weighting λ parameters, different nondominated solutions are found. On the other hand, the ϵ -constraint method is set up as:

$$\left\{ \begin{array}{ll} \arg \min_w & \mathbf{w}'\Sigma\mathbf{w} \\ \text{subject to} & -\mathbf{w}'\boldsymbol{\mu} \leq -\epsilon_1 \\ & -\mathbf{w}'\boldsymbol{\gamma} \leq -\epsilon_2 \\ & \mathbf{w}'\mathbf{1} = 1 \\ & 0 \leq w_i \leq 1 \quad \forall i \in (1, \dots, N), \end{array} \right. \quad (3.12)$$

where different nondominated solutions are found by the variation of ϵ values.²³ The output generated by both methods is a set of points spanning a three dimensional efficient surface, that also may be represented by contour lines of the same level of one goal. In order to simulate a portfolio selection, Lundström and Svensson (2014) conduct a typification of investors according to a set of criteria. Each hypothetical investor fixes first a percentage value for one of the goals, which determines the location on the minimum / maximum interval of that specific goal. Then for a second goal either the minimum or the maximum is chosen. Specifying a third criterion is redundant, since every portfolio is uniquely determined by two criteria. According to this, an exemplary investor might feature preferences as ESG:75%, Volatility: 'Min', Expected Return: 'none'.

Similar to Lundström and Svensson (2014) Hirschberger et al. (2013) suggest a tri-criterion method. The a-priori approach is chosen to incorporate an additional ESG criterion similar to Lundström and Svensson (2014), yet the way of generating the efficient frontier is somewhat more sophisticated. Instead of applying ϵ -constraints, here the nondominated surface is computed analytically. While the nondominated MV set technically is a collection of curved archs, the nondominated surface is a collection of curved platelets rather than a collection of single points (s. Figure 3.1). Hirschberger et al. (2013) compute polyhedra called *stability sets* to construct the nondominated surface. The underlying initial problem is given in Appendix A.10. The latter is condensed into the

²³ In Lundström and Svensson (2014), Problems 3.11 and 3.12 are solved by using the *quadprog* algorithm of the commercial software *Matlab*. Quadprog is a solver based on either an active-set strategy or an interior reflective Newton method (Geletu, 2007)

maximization problem

$$\begin{cases} \arg \max_w & -\mathbf{w}'\Sigma\mathbf{w} + (-\mathbf{c}_1 + \lambda_2 \mathbf{c}_2 + \lambda_3 \mathbf{c}_3)'\mathbf{w} \\ \text{subject to} & \mathbf{w} \in S, \end{cases} \quad (3.13)$$

where \mathbf{c}_1 stems from including a lower bound constraint directly in the maximization problem, \mathbf{c}_2 is defined as a vector of expected returns and \mathbf{c}_3 is a vector of quantities attributed to some third goal. The vector $\boldsymbol{\lambda} = (-1, \lambda_2, \lambda_3)$ with $\lambda_2, \lambda_3 \geq 0$ is defined as the weighting vector. In contrast to the weighted sum approach necessitating a dispersion of different points of (λ_2, λ_3) , Hirschberger et al. (2013) construct the efficient surface applying the *Karush-Kuhn-Tucker-Conditions* in a parametric pivoting procedure.

In an empirical evaluation, Hirschberger et al. (2013) implement the developed algorithm to a problem linked to sustainable investing as the third objective dimension. For this purpose the ESG score is defined as the third goal \mathbf{c}_3 to maximize. To generate single portfolios which are empirically compared to funds in the market, hypothetical investors with different pairs of λ_2 and λ_3 weightings are assumed. As opposed to Lundström and Svensson (2014) the minimization of volatility is assumed as a fixed goal, such that an investor with $(\lambda_2, \lambda_3) = (0, 0)$ considers the minimum variance portfolio as optimal allocation.

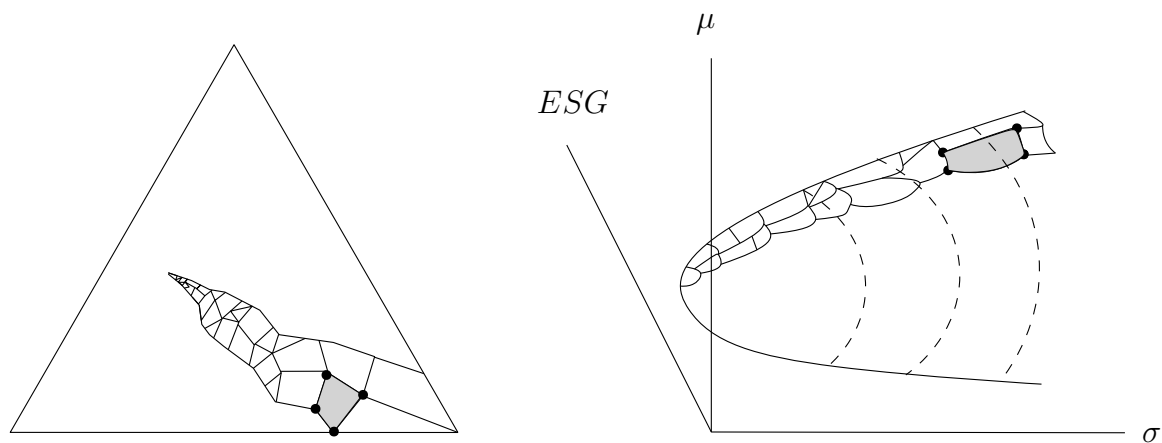


Figure 3.1 – This illustration shows the efficient set in S on the left hand side and the plateletwise hyperboloidic nondominated set. The feasible space on the left is more of a portrait of S since for an asset space of $N > 3$ assets, which is usually the case, there is no visual representation for S . The efficient set in S consists of polyhedral subsets, platelets. The latter are projected into the objective space and form the nondominated surface composed of hyperboloidic platelets. The grey platelets are correspondents and visualize the projection. The three goals on the right clockwise are the (expected) ESG-score, the expected return and the standard deviation. (Source: own figure based on Steuer et al. (2008))

3.4 Multi-Objective Optimization and Fuzzy Logic

A further approach linked to MOOP is covered in Bilbao-Terol et al. (2012), combining MOOP and fuzzy logic. The decision here is modelled as a fuzzy goal programming approach with three main criteria groups: (i) the expected return of the portfolio; (ii) the return of the portfolio in each past and future period since the tracking error with respect to a certain benchmark is relevant and (iii) the imprecisely known investor preferences about RI features of the titles. Fuzzy logic is to be understood as alternative to boolean logic with values of variables being either true (1) or false (0). It allows for values to lie between 0 and 1, i.e. to belong to a specific set to a certain degree. The latter is formalized by means of a membership function $\nu_{\tilde{A}}$ that attributes a degree of possibility for a variable x out of the universal set X to be in the fuzzy set \tilde{A} . A fuzzy set \tilde{A} is thus a set of ordered pairs, often written as $\tilde{A} = \{x, \nu_{\tilde{A}}(x) \mid x \in X\}$. Furthermore, a real fuzzy number \tilde{N} on \mathbb{R} is defined by a upper and semi continuous membership function $\nu_{\tilde{N}} : \mathbb{R} \rightarrow [0, 1]$. In Bilbao-Terol et al. (2012), a trapezoidal fuzzy number is applied, where the membership function is linearly increasing on a defined interval $[n_1, n_2]$, equal to one on $[n_2, n_3]$ and decreasing on $[n_3, n_4]$. Fuzzy numbers may also be understood as possibility distributions (Bilbao-Terol et al., 2012). For the portfolio selection

model a standard MOOP is set up. For every objective function, the decision maker defines goals, s.t. the found solution is closest to the defined goals. Hence, this approach provides not an optimization, but rather finds a *good enough* solution. The expected return of any asset is modeled as a fuzzy number $\tilde{E}(R_i)$ based on historical realizations of asset returns and fuzzy weights stemming from an expert's input. This procedure, also called *expert system*, reflects the general view that expected returns cannot be estimated confidently, but a set of possibility values can be attributed to different future realizations of the returns. Portfolio return itself as a weighted sum of the single expected returns is again a fuzzy number. As the optimization applied in this paper minimizes deviations from some ideal goal, a vital task is the determination of the target value. In case of expected portfolio return²⁴ $\tilde{E}_p = \tilde{E}x$, to this end the ideal fuzzy number E_0^{*R} representing portfolio return results from the maximization of the portfolio return under a set of feasible constraints (long only, weights sum up to unity). The authors apply a method to minimize the undesirable negative deviation of the final portfolio from the upper end of the fuzzy number interval belonging to the ideal target return. To this end, formally the fuzzy goal as defined as the fuzzy inequality condition $\tilde{E}_p = \tilde{E}x \gtrsim \tilde{E}^*$ turns into the non-fuzzy goal $E_0^L \geq E_0^{*R}$, which for the sake of the minimization of deviations becomes the equality constraint $E_0^L x + n_E - p_E = E_0^{*R}$, with n_E and p_E as deviation variables.²⁵ Deviation by the nature of the constraint will be undesirable negative, since the benchmark is the right side border of the maximization of E_p . Similarly the negative deviation of the portfolio return from a benchmark index as reference point for some finite amount of forecasting periods is aimed to be minimized. As a third goal, ESG performance is addressed by the requirement of a minimum fraction m of the total budget invested in assets that are socially responsible, i.e. $\sum_{i=1}^n x_i \gtrsim m$. This is expressed in terms of the following membership function:

$$\mu_{SR}(x) \begin{cases} 0 & \text{if } \sum_{i=1}^n x_i < m - h \\ \text{strictly monotonically increasing} & \text{if } m - h \leq \sum_{i=1}^n x_i \leq m \\ 1 & \text{if } \sum_{i=1}^n x_i > m \end{cases} \quad (3.14)$$

²⁴ Where $\tilde{E}x = \sum_{i=1}^n R_i x_i$ and x_i is the portfolio weight.

²⁵ The lower 0 index denotes the α -cuts; for $\alpha \in [0, 1]$ the α level set is a set $N_\alpha = \{x \in \mathbb{R} \mid \mu_{\tilde{N}}(x) \geq \alpha\}$, which is a closed bounded interval denoted by $[n_\alpha^L, n_\alpha^R]$.

where h in Expression is the tolerance threshold as set by the investor. The final goal programming model puts weights on each of the three goals and minimizes the overall sum of deviations under the feasible set of constraints of all fuzzy goals simultaneously. At the bottom line, this is what qualifies fuzzy goal programming as an adequate approach to the ESG incorporation problem: it allows for defined goals being treated as soft constraints causing deviations to be allowed but minimized. This procedure generates the best among all acceptable goals for the decision maker.

3.5 MV Optimization with an Additional Linear Constraint

Drut et al. (2010) address the task of quantitative ESG incorporation into portfolio optimization in a straight forward way and introduce a linear constraint to the classical Markowitz model. As a starting point, recall the classical MPT Problem 3.5 from Section 3.2.2:

$$\begin{cases} \arg \max_w & \mathbf{w}'\boldsymbol{\mu} - \frac{\rho_i}{2}\mathbf{w}'\boldsymbol{\Sigma}\mathbf{w} \\ \text{subject to} & \mathbf{w}'\mathbf{1} = 1 \end{cases}$$

In this context, the solutions to Problem 3.5 form the *Social Responsibility (SR) insensitive* efficient frontier in the μ, σ plane. The SR rating of a portfolio is introduced as $\phi_p = \mathbf{w}'\boldsymbol{\phi}$ with the vector of single ratings $\boldsymbol{\phi} = [\phi_1, \phi_2, \dots, \phi_n]$. This implies the necessary assumption that the rating is additive, i.e. the dot product is meaningful as the weighted sum of ratings equals the portfolio rating. The analytic solution of the Langrangian of Problem 3.5, i.e. the optimal MV portfolio in a universe without a riskless asset,²⁶ for the weight vector \mathbf{w} is multiplied with the vector of the SR ratings $\boldsymbol{\phi}$. As the portfolio return $\mathbf{w}'\boldsymbol{\mu}$ and the portfolio's social responsibility rating $\mathbf{w}'\boldsymbol{\phi}$ are both linear functions of $\mathbf{1}/\rho_i$, where ρ_i is the risk aversion parameter of investor i , the rating of the portfolio can be rearranged into the linear relation

$$\phi_p = \delta_0 + \delta_1\mu_p \tag{3.15}$$

with μ_p being the expected portfolio return and δ_0 and δ_1 , both determined by the variables $\boldsymbol{\mu}$, $\boldsymbol{\phi}$ and $\boldsymbol{\Sigma}^{-1}$.²⁷ As Expression 3.15 is derived from the optimal solutions, it delivers the SR ratings

²⁶ See e.g. Zuber (2012), Appendix A3 for a detailed derivation of the solution.

²⁷ For details, see Drut et al. (2010).

of any portfolio lying on the SR insensitive efficient frontier. The sign of δ_1 can be both, positive or negative; for instance the portfolios with highest returns may belong to the best or worst SR rated portfolios. In other words, given by the logic of the efficient frontier, if $\delta_1 > 0$, riskier optimal portfolios (higher return) get better, if $\delta_1 < 0$ riskier portfolios get worse SR ratings. Allowing for investors being sensitive to the SR rating of their portfolio the optimization problem is now defined as follows:

$$\begin{cases} \arg \max_w & \mathbf{w}'\boldsymbol{\mu} - \frac{\rho_i}{2}\mathbf{w}'\boldsymbol{\Sigma}\mathbf{w} \\ \text{subject to} & \mathbf{w}'\mathbf{1} = 1 \\ & \phi_p = \delta_0 + \delta_1\mu_p \geq \phi_i \end{cases} \quad (3.16)$$

with ϕ_i as the required minimum SR rating level of investor i . For solving Problem 3.16, an approach developed by Best and Grauer (1990) following parametric quadratic programming methods is applied. As a consequence of the additional linear constraint, the shape of the (SR-sensitive) efficient frontier may alter depending on the sign of δ_1 and on the threshold value ϕ_i . The authors distinguish between four different cases, which correspond to the combination of (i) the sign of δ_1 and (ii) the \leq relation of ϕ_i to some endogenously given level ϕ_0 . Either the SR sensitive and insensitive frontiers do not differ at all, are congruent above (below) a specific corner portfolio and divergent below (above) it or show no congruence at all. In any case, a deviation from the SR insensitive efficient frontier results in a less efficient solution, i.e. in this model depending on the constraint defined by the investor responsible investment comes at the cost of abandoning efficiency to a certain degree. Also, the authors emphasize that the height of that cost depends largely on the risk aversion parameter of the investor. For instance, if only the right portion of the SR sensitive efficient frontier is penalized, only low risk-aversion investors exhibit higher cost. Generally, a similar trade off between SR and MV efficiency results, when a riskfree asset is introduced, altering the position of the tangential portfolio according to the relocated SR sensitive efficient frontier.

(Jessen, 2012) develops two methods, one of which features an additional linear constraint to MV optimization similar to Drut et al. (2010). Yet, the problem is tackled via the minimization of portfolio variance maintaining the constraints of a given expected return and a specific level of *portfolio responsibility*, which is a weighted sum of k ESG criteria for N assets. The difference to Drut et al. (2010) is that there is no individual risk aversion parameter taken into account. Jessen

(2012) solves the minimum variance analytically by means of Lagrangian multipliers. The absence of the necessity to specify ex ante preferences of an investor is considered as advantageous as opposed to utility driven approaches .

3.6 Utility Theory Based Approaches

A possible way of quantitative integration of ESG criteria into portfolio construction is tackling the problem via utility theory. Although the utility conception is generally an integral part of portfolio optimization, Jessen (2012) focuses on utility theory as a method. In this approach it is assumed that a set of ESG factors have some economic intuition and should be incorporated into a Von Neumann Morgenstern (VNM) utility framework (s. also Appendix A.5) with respect to institutional investors. The VNM utility has the most general functional form $u : \mathbb{M} \rightarrow \mathbb{R}$, where \mathbb{M} is the domain of all possible outcomes. In the more specific setup of this approach the utility function maps investment return x and portfolio responsibility s to some utility quantity in the set of real numbers $u : (x, s) \mapsto \mathbb{R}$. An investor's utility function with respect to financial return is assumed to be monotonic, quasi-concave, continuous and globally nonsatiated, which means that more wealth is preferred, yet marginal utility diminishes, the higher returns are. Also, the investor is assumed to be risk-averse. As the feasible portfolios are bounded by no-short-selling constraint, the domain is defined as $\mathbb{M} = [-1, \infty) \times [-1, 1]$. According to Jessen (2012) an investor is considered a responsible investor if

$$\forall \{s_1, s_2\} \mid s_1 \geq s_2 : u(x^*, s_1) \geq u(x^*, s_2) \quad (3.17)$$

where $x^* \in [-1, \infty)$ and $s \in [-1, 1]$ and u is an increasing utility function as described above. This implies that greater portfolio responsibility is able to generate more utility ceteris paribus, that is

$$u(x^*, s_1) = u(x^*, s_2) + \Delta_u \quad (3.18)$$

with $\Delta_u > 0$ and $s_1 > s_2$ or equivalently

$$u(x^*, s_1) = u(x^* + \Delta_r, s_2) \quad (3.19)$$

with Δ_r as the return premium that is required to compensate the lesser utility due to the lower portfolio responsibility. Note, that the amount of Δ_u is not comparable across different utility

functions, Δ_r on the opposite is. Jessen (2012) makes some examples of functional utility forms, starting with the generalized affine combination

$$u(x, s) = (1 - \alpha)u_1(x) + \alpha u_2(s) \quad (3.20)$$

where $\alpha \in [0, 1]$ is the weight the investor attributes to utility coming from portfolio responsibility as compared to utility from the financial outcome. The functional form of u may be for example

$$u(x, s) = (1 - \alpha)\ln(x + 1) + \alpha\ln(s + 1) \quad (3.21)$$

where \ln is the natural logarithm function, the addition of 1 to is due to the logarithm function only being defined for inputs greater than zero. An interesting form of utility is proposed in another example inspired by the Prospect Theory value function of Kahneman and Tversky (1979). It is s-shaped asymmetric regarding the s -component with the symmetry axis crossing $s = 0$, some utility if $s \geq 0$ and disutility if $s < 0$. It reflects that deviations from the reference point $s = 0$ may be translated into units of utility in different ways. Jessen (2012) points out that the form of u usually has to be assumed and may not be estimated. Yet, it is argued that this might be a problem for the retail investor. Institutional investors, however, might develop their own methods to specify a utility function.

3.7 Splitting Methods

There are several approaches that split the portfolio selection problem in some way. Hallerbach et al. (2004) propose a framework to find the optimal portfolio in interaction with the ESG concerned investor. Therefore every security in the asset universe is characterized by k attributes, for instance *governance* or *employees labor rights*, but also financial attributes as *book to market value* or *total return*. In a first step under the constraint of some general maximum portfolio weight per stock, feasible portfolios each with one of the attributes maximized (for the sake of simplicity) are found in a multiple goal programming framework. The investor is then confronted with the feasible portfolios and asked to choose the most acceptable. If there is none, then the minimum requirements have to be adjusted to generate a new set of feasible portfolios with respective values. While this procedure may be potentially circuitous, on the upside there is no beforehand specification of investor's preferences

needed.

A rather unconventional two-step approach is developed by Bilbao-Terol et al. (2013) featuring a hedonic pricing method that provides the maximum level of financial satisfaction in the first stage, followed by the second stage selecting the portfolio of the best social and financial portfolio with the portfolio from the first step acting as benchmark. The hedonic pricing model assumes that the price of a good is linearly depending on a set of attributes of this good driving the price. In Bilbao-Terol et al. (2013), the exposure of the portfolio to a specific factor (e.g. labor rights) is expressed as a weighted average of the exposure of all assets in the portfolio:

$$SR_f(\mathbf{w}) = \sum_{i=1}^n pt_{if} P_{iT} x_i \quad (3.22)$$

where \mathbf{w} is the portfolio weight vector, pt_{if} is the score of asset i on attribute f and P_{iT} is the price of asset i at investment date T . The objective that is maximized in the portfolio selection process is

$$SR(\mathbf{w}) = \sum_{f=1}^F h_f^* SR_f(\mathbf{w}) \quad (3.23)$$

where h_f^* denotes the hedonic price of attribute f . It is generated by means of an empirical hedonic regression. The generic portfolio selection model consists of maximizing the Expected Value at the End of the Period (EVE), maximizing SR as in Equation 3.23, and minimizing some Risk Measure RM , which either could be the portfolio variance or the conditional value at risk (potential downside). The problem is then split into two stages. Stage 1, the maximization of financial wealth is conducted in two steps. (i) minimizing RM and maximizing EVE subject to the usual constraints (no short-selling, whole budget invested) by means of an ϵ -constraint method (see also Section 3.3) to approximate the efficient frontier; (ii) to obtain the portfolio that optimizes the financial needs of the investor the *certainty equivalent* is applied. The latter is often applied in practice to quantify utility, it is the amount paid with certainty yielding the same utility as the expected utility of the risky allocation (see also Appendix A.7). Obviously, this requires the assumption of some specific functional form of utility. To form expectations over asset prices Bilbao-Terol et al. (2013) conduct a Monte Carlo simulation. The portfolio with the highest expected utility, and thus the highest certainty equivalent is chosen and specified by EVE^* and RM^* . Thereafter, in stage 2, an ϵ -constraint method is used to maximize $SR(\mathbf{w})$ implementing bounds as constraints that are close to EVE^* and RM^* . Also, the possibility of shifting the bounds in interaction with the investor is

given in this approach.

Instead of splitting the optimization process as described above, there are also approaches to split the asset universe. Ballestero et al. (2012) group the securities being candidates for a portfolio into ethical assets, and those that are not considered as such. Mathematically, this is implemented in defining the two subsets of S^* of h ethical assets and $m - h$ remaining assets that are only characterized by financial criteria. This approach also addresses a goal programming problem by minimizing the portfolio variance. Yet the problem of incorporating lies in the formulation of the constraints:

$$\sum_{i=1}^m w_i \mu_i \geq g_0 \quad \text{and} \quad \sum_{i=1}^h w_i \mu_i \geq e_0 \quad (3.24)$$

where g_0 is the minimal goal defined for the portfolio return of the non-ethical assets and e_0 for the assets. The investor then specifies some $\lambda \in [0, 1]$ expressing the aspiration level for ethical goals in order to determine $e_0 = \lambda \mu_{max}$, where $\mu_{max} = \max(\mu_1, \mu_2, \dots, \mu_h)$. This requires a distinction of two cases: (i) if $\lambda = 1$ there is exactly one solution, namely $x_p = 1$ for p being the index assigned to μ_{max} , i.e. the decision maker invests her whole money into asset p ; (ii) if $0 \leq \lambda_0 < 1$, the higher λ_0 the higher the ethical target. This second case implies that $\sum_{i=1}^h w_i = q \geq \lambda_0; q \leq 1$. The logic behind this argument follows directly from the definition of e_0 and the right hand side constraint of expressions 3.24: provided weights $w_i \in [0, 1]$ and the specific choice λ_0 , since the weighted sum of any vector $\boldsymbol{\mu}$ is less than its maximum and the constraint requires the left hand side to be at least equal or greater than e_0 , $\sum_{i=1}^h w_i$ must be at least equal or greater than λ_0 . That is, the choice of λ also determines $1 - q$, the proportion of the sum of weights of the non ethical assets, since it is assumed that $\sum_{i=1}^h w_i + \sum_{i=h+1}^m w_i = 1$. Thus, the incorporation of ethical preferences is achieved by splitting the asset universe and shaping the constraints accordingly. Besides the input of λ , in Ballestero et al. (2012) also the investor's Absolute Risk Aversion (ARA) coefficient for both subsets of assets have to be estimated.

3.8 Nonfinancial Return Approaches

The concept of a social return on investment and the blending of social and financial value is elaborately discussed in Emerson (2003). An implementable way of incorporating so called sustainable

returns into portfolio return is e.g. discussed in Dorfleitner and Utz (2012) and Dorfleitner et al. (2012). These contributions following both, a MV- as well as a *saftey first* approach, treat the value generated by investing responsibly similar to the financial value and thus optimize not only with regard to the financial return but also to return in terms of responsibility. That means in particular that the MV nature of financial returns based on their stochastic character is adopted to the sustainability of investments. In Dorfleitner et al. (2012) it is assumed that an investor receives at the end of a period a financial payoff of $v_0(1 + R)$, where v_0 is the initial value and R is the financial return, as well as $v_0 * S$ with S as the non-monetary social return. A portfolio A is considered as efficient if there is no portfolio B such that

$$1) \mu_{R_A} \leq \mu_{R_B}; \quad 2) \mu_{S_A} \leq \mu_{S_B}; \quad 3) \sigma_{R_A} \geq \sigma_{R_B}; \quad 4) \sigma_{S_A} \geq \sigma_{S_B}; \quad 5) \sigma_{R_A, S_A} \geq \sigma_{S_A, S_B}, \quad (3.25)$$

with at least one strict inequality, where μ and σ stand for the corresponding expected portfolio return and standard deviation. The fifth condition is expressed in terms of the covariance of the financial return with the social return, stating that portfolios with low covariances are preferred. The argument therefore is that with a low or negative covariance, an investor may get comfort in high social returns, when financial returns are low. In order to formulate an investment goal, Dorfleitner et al. (2012) consider two approaches, either to aggregate financial and social goals or to formulate preferences for the two of them. The efficient frontier is found solving the following optimization problem:

$$\begin{cases} \arg \max_w & \beta_1 \mu_{R_P}(\mathbf{w}) + \beta_2 \mu_{S_P}(\mathbf{w}) - \beta_3 \sigma_{R_P}^2(\mathbf{w}) - \beta_4 \sigma_{S_P}^2(\mathbf{w}) - \beta_5 \sigma_{R_P, S_P}(\mathbf{w}) \\ \text{subject to} & \mathbf{w}'\mathbf{1} = 1 \end{cases} \quad (3.26)$$

with β_i being a preference factor for goal i and $\beta_3 = 1$ for redundancy reasons. The aspect of covariances deserves attention, since for every pair of assets i and j six of them determine the optimal solution: the financial covariance σ_{R_i, R_j} , social covariance σ_{S_i, S_j} , financial and social intra-asset covariances σ_{R_i, S_i} and σ_{R_j, S_j} , financial and social inter-asset cross-covariances σ_{R_i, S_j} and σ_{S_i, R_j} . The solution to Problem 3.26 is found by solving a Lagrangian, and there is a unique solution if the matrix that comprises all covariances is invertible. Also, the solution depends on the four preference parameters, i.e. \mathbf{w} is a mapping of \mathbb{R}_+^4 to the efficient set $\mathbb{E} \subset \mathbb{R}^5$. Dorfleitner et al. (2012) consider also a simplified model with deterministic social returns with a remaining μ - S - σ efficiency, the starting point of which is equal to Problem 3.26 with $\beta_4 = \beta_5 = 0$. Introducing a riskless asset

in reference to Tobin (1958) whereby the risk aversion coefficient determines the proportions of the tangential portfolio and the riskfree asset in the original version, it is proven in Dorfleitner et al. (2012) that there is no specific tangential portfolio, since the optimal risky portfolio depends on the β -preferences.

3.9 Weight Shifting Approaches

A straightforward way to include ESG considerations in portfolio optimization is the adjustment of some benchmark's weights due to ESG properties of the assets to invest in. The method developed in Chapter 4 of the present thesis may be categorized as such an approach. In a practitioner oriented publication, Nagy et al. (2013) aim to achieve an ESG-tilt to a portfolio, thus to improve ESG ratings while maintaining risk, performance, country, industry and style characteristics of some benchmark portfolio. This is achieved through two different strategies: (i) a tilt-strategy overweighting assets exhibiting high ESGscores and underweighting the ones with low scores and (ii) an ESG-momentum approach where the portfolio weights depend on the change of the ESG scores. The paper, however, focuses on empirical results advocating such strategies rather than discussing the optimization methods applied. It is mentioned that the starting position is a market capitalization weighted portfolio the weights of which are modified accordingly. It remains unclear how these weights are shifted, yet, the referential market portfolio might hint at a Black-Litterman Model (BLM) based method. Another example of portfolio weight shifting in a practitioner's context is given in UNPRI (2016a), where ESG scores are assumed to cover risk characteristics that are not captured by pure volatility. The authors claim to having devised a systematic way to incorporate the modified risk profile of a poor ESG performer into portfolio construction, but refrain from discussing the method. Similar to the method proposed in Chapter 4, Quigley (2009) makes use of the Asset4²⁸ ESG score database to penalize assets with low ESG scores and favor such with high scores within the portfolio optimization process. Additionally, the bottom score quintile of the assets is eliminated from purchase consideration. For the implementation Quigley (2009) follow a dual benchmark strategy, where the benchmarks act as reference portfolios for the optimized portfolio to be consistent with

²⁸ The Asset4 database is an ESG database considering more than 250 key performance indicators provided by Thomson Reuters.

the predetermined level of market capitalization as well as to reduce the tracking error as defined by optimization inputs.

The approach that is closest in terms of methodology as compared to the proposed method from Chapter 4 is presented in Brandstetter and Lehner (2015) applying a modified BLM to incorporate ESG measures. It is addressed to the portfolio management of institutional investors asking for methods to account for ESG criteria other than through negative screening. To make a clear distinction between the here proposed method and Brandstetter and Lehner (2015), it is essential to understand the basic functionality of the BLM. In principle the BLM allows to reconstruct the market portfolio and to adjust the portfolio according to the inputs of the decision maker. The later quantifies *investor views* by means of the view vector Q making statements about the expected (relative) performance of the single assets in the portfolio. Additionally, in a covariance-like matrix Ω , the degree of certainty about these views is added as an input to the mode. Brandstetter and Lehner (2015) use Q and Ω to address the incorporation of ESG scores in alienating Q and assigning ESG risks via Ω . However, in doing so, some of the main features of the BLM, namely to express and involve an investors views and the uncertainty about them are dropped. On the opposite, the method proposed in Chapter 4 maintains these features and instead blends a structured diagonal matrix of ESG linked penalizing / rewarding quantities with the posterior covariance matrix as generated through the standard BLM process. In general, weight shifting approaches may be more pragmatic in an institutional investors environment, providing a moderate way of incorporating ESG considerations and thus preventing portfolios from being potentially under-diversified.

3.10 Discussion

The previous sections outline several approaches to address the problem of the integration of quantitative ESG considerations into portfolio construction and management in a quantitative manner. As by the nature of the problem, optimizing portfolios with respect to financial criteria while considering non-financial criteria as well, multi-objective goal programming is obviously appropriate and most of the screened publications refer to it in some form. Non-financial optimization is mostly linear while variance minimization adds a quadratic programming optimization component to the MOOP.

Judging from the different approaches tackling the problem by MOOP solving strategies studied for this thesis, there seems to be an accumulation of ϵ -constraint type methods. Also, Markowitz is cited in almost every approach, which is an indication of the MPT framework conceptualizing the trade-off between financial return and risk in a way that is widely adopted among scholars as well as practitioners. Many approaches may be interpreted as just an expanded version of the MPT. Mathematically, in general, Markowitz-like minimum-variance optimization problems as analyzed above are smooth, non-linear and convex, which implies that local minima are also global minima. Such problems can be solved with Lagrangian techniques. The problem of ESG integration may be solved integrally in an overarching approach, or split into sub-problems. This duality may evoke the necessity of a categorization of the different approaches in scope. Yet, this endeavor may not lead to meaningful results, as the approaches share many components and differ non-systematically. In principle, portfolio optimization considering ESG factors is addressed in most of the cited sources by defining some non-dominated set of potential portfolios with respect to the involved criteria and then finding a solution fitting an investor's requirements. While the non-dominated set is by no means bounded to three goals (mean, variance, ESG), this setup is chosen by most authors. This goes along with some benefits, for instance a manageable complexity and also the possibility to visualize the non-dominated set in the three dimensional space. In order to fulfill the quantification of an investor's views or needs, often some specification of preference parameters is needed to either scalarize the objective function, i.e. to generate a single objective function including multiple goals, or to find portfolios iteratively or approximately. There are also sources emphasizing the potential difficulty to define specific functional forms for utility. Besides modeling utility, also the application of multiple linear constraints is common. Another similarity among the papers in scope is the use of some ESG score or rating in order to quantify the responsibility dimension, often provided by professional providers, sometimes based on a proprietary set of rules. Apparently, ESG scores are treated either as stochastic variables, which is consistent with the Markowitz framework where the object of the optimization are expected values, or as deterministic values. The different approaches studied for the completion of the present thesis also exhibit different grades of granularity in defining ESG preferences; some bundle all RI aspects into one single score, some feature preferences for different sub-categories. Often, a weighted sum of the asset's ESG scores is defined as the portfolio

ESG measure. There are also strategies incorporating the change in scores within the past period. The way of how an ESG strategy is implemented is also different depending on the assumptions on how responsible investing influences the portfolio performance. For instance, if MPT is applied in a very strict way, then every restriction to the portfolios lying on the efficient frontier goes along with an abandonment of efficiency resulting in inferior frontiers. That is, the responsible investor has to be willing to concede financial return from this point of view. Yet, there are also approaches that assume superior risk adjusted returns linked to ESG compliant investments, penalizing low performing titles in terms of ESG and favor top performers. It is noticeable that most of the papers do not specify *the investor*, which is in most economic applications a reliable method, when it is referred to the generic *representative investor*. However, as discussed in Section 2.3, the demand for a systematic ESG integration is to be found in the institutional sector rather than by private investors. Yet, prevalently there seems to be a gap between the specific needs of this investor category, i.e. for instance benchmark reference or the conceptual proximity to MV principles, and the solutions provided in literature. This may not be helpful to overcome barriers hindering such investors from incorporating ESG measures more systematically. More practitioner oriented approaches as Nagy et al. (2013), Quigley (2009), Brandstetter and Lehner (2015) or the method proposed in Chapter 4 try to fill this gap.

A Black Litterman based Approach

The following chapter proposes a method based on the Black Litterman Portfolio Optimization Model. It discusses the basic concepts in Section 4.1 and develops the incorporation of ESG criteria in Section 4.2

4.1 The Black Litterman Model and its elementary Components

4.1.1 Market Equilibrium

As the BLM is an equilibrium based model, it is important to understand what kind of market equilibrium is referred to. In a nutshell: the Capital Asset Pricing Model (CAPM) as a cornerstone of financial theory with its foundation laid by Sharpe (1964), Lintner (1965) and Mossin (1966) models a market with an economy of agents, all investing according to the principles as defined in the MPT (Markowitz, 1952) and the separation theorem (Tobin, 1958) (see Section 3.2.2). As any investor in such an economy is rational in the sense of a Markowitz setup, there is only one optimal portfolio of risky assets, namely the tangential portfolio. According to the investor's own risk preferences and due to the separation theorem, there are three possible ways to be invested in this economy. (i) To be fully invested in the tangential portfolio; (ii) to hold some linear combination between holding the riskfree asset and the tangential portfolio (and as not the whole wealth is invested in the tangential portfolio lending money to other agents at the riskfree rate); (iii) holding more than 100% of the

tangential portfolio, i.e. borrowing at the riskfree to buy the tangential portfolio. Aggregated over the whole economy, the market is said to be complete and to clear, the borrowing and lending part cancel out and the agents hold mutually the Market Portfolio (MPF). This is an obviously simplified view based on some assumptions: all market participants share the same expectations about future cash flow coming from the assets at the end of the investment period, implying also that all investors plan for the same holding period. It is also assumed that investors in the CAPM economy are price takers, that is their trading on the market remains without impact on the prices. Moreover, it is assumed that the market contains all publicly tradable assets, and asset returns are assumed to be normally distributed. A further simplifying assumption is the lack of taxes and transaction costs.

One of the key statements of the CAPM is that the only risk an investor gets compensated for is the market risk, also known as systematic risk. That is, the expected return of any asset j in the market is a linear function of the co-movement of that asset with the market, while the idiosyncratic, non-systematic risk is irrelevant for the return as it is diversifiable. This relationship is expressed as follows:

$$\mu_j - R_f = \beta_j(\mu_M - R_f) \quad (4.1)$$

where μ_j is the expected return of asset j , R_f is the riskfree rate, $\beta_j = \frac{\sigma_{j,M}}{\sigma_M^2}$ the fraction of covariance of the returns of asset j with the market return in the nominator and the market variance in the denominator.²⁹ A graphical representation of the equilibrium and β measure reasoning is given in Figure C.4 in Appendix C.

However, for the derivation of the BLM the β logic is secondary, but the market clearing in the equilibrium at the beginning of the investment period is vital. As by equilibrium considerations, the price of each asset is determined since the market capitalization³⁰ is endogenously given. This is due to the identity of the weight of asset k in the individual portfolio of every single agent and thus the market share of asset k in the MPF. Based on this equilibrium logic (see Appendix A.11 for details) the vector of expected returns can be defined as

$$(\boldsymbol{\mu} - R_f \mathbf{1}) = \frac{(\mu_M - R_f)}{\sigma_M^2} \boldsymbol{\Sigma} \mathbf{w}_M \quad (4.2)$$

²⁹ See Appendix B.3 for a derivation of Expression 4.1.

³⁰ Market capitalization refers to the value of an asset relatively to the value of the whole market: $MC = \frac{S_k n_k}{\sum_{k=1}^K S_k n_k}$, where S_k is the asset price (per share) and n_k is the number of shares outstanding of asset k .

where Σw_M is the matrix product of the covariance matrix Σ and the vector of MPFweights, resulting in a vector of n covariances of the single assets with the market portfolio in the n asset case.³¹ Equation 4.2 marks the link between the CAPM and the BLM, it is referred to in the following subsection.

In addition to making rather strong assumptions, the validity of the CAPM has been subject to criticism since the early years of its existence. The Fama-French framework (Fama and French, 1992) and its numerous variations agree in principle that the asset return is contingent on market movements, yet it is claimed that other factors as the Book-to-Market ratio and alike may explain asset returns as well (see Appendix A.1). A famous critical appraisal of the CAPM is given in Roll (1977), where it is proven that the validity of the linear relationship between β and the return is not empirically testable unless the real market portfolio (including every single asset in the whole asset universe) is known, which is very unlikely to be the case. On the other side, the CAPM is still widely referred to in academia as well as in practice and there is also a vast literature attesting the theory to be *alive and well* (e.g. Jagannathan et al. (1993)).

4.1.2 General Overview of the BLM

Despite the MPT being a cornerstone in financial theory and convincing in its simplicity, it exhibits drawbacks in practical implementation. Already early critical publications (e.g. Michaud (1989)) detected the Markowitz portfolio optimization method to provide financially meaningless optimal portfolios. So called *corner solutions*, where out of the asset universe only very few assets are held in the optimal portfolio, effectuate sincere diversification insufficiency. Also, Michaud (1989) criticizes the sensitivity of MV optimization causing the optimizer to magnify small estimation errors. Mainly based on these flaws, in the early 1990s Fischer Black and Robert Litterman aimed to develop a framework that would adopt the principles of the MPT and the CAPM with the goal to make the standard optimizer better behaved (Litterman, 2004). In fact, the model is a reformulation of the investor's decision problem, that may be laid out in a frame of Bayesian logic. At the initial position there are estimates of expected asset returns as implied by the market capitalization. This is based on CAPM equilibrium considerations as a part of the *prior distribution* or simply the Bayesian *prior*.

³¹ Note, that it is straight forward to link Equation 4.2 to the β argumentation, see also Appendix A.11.

In a second stage the investor may define *views*, that are statements on the performance, thus the expected returns and also return differentials among the single assets being held in the portfolio. Moreover, these views can be attributed with degrees of uncertainty. Views and uncertainty together lead to the *conditional distribution*. The blending of these view-inputs with the prior results in a posterior distribution, which serves then as input in a common MV optimizer. For an overview of the inputs and distributions see Figure 4.1. Obviously, in addition to the assumptions being inherently made by reference to the CAPM and the MPT, the premise that an investor is able to outperform the market with private information or skills requires the assumption of a semi-strong form of market efficiency (Cheung, 2010). Moreover, it is assumed that returns are normally distributed (as in the standard MPT) and the distribution of the prior as well as the conditional distribution are known.

There is an extensive body of literature dedicated to the BLM. As Fischer Black and Bob Litterman were rather brief concerning the explanation of their model and a detailed discussion of respective assumptions in Black and Litterman (1992), there were several follow-up papers of in-depth analysis and clarification of the model, e.g. He and Litterman (2002), Satchell and Scowcroft (2000) or Christodoulakis (2002). The latter provides important insights to the model from a Bayesian perspective. Bevan and Winkelmann (1998) focus empirically on the practicability of the model and deem it appropriate to incorporate a portfolio manager's views. Moreover, there are numerous publications that modify the original model in some way, be it in terms of relaxing assumptions as in Meucci (2005), or Cheung (2013) incorporating additional risk factors, or Harris et al. (2016) with a time-varying, dynamic implementation of the model. To date, in an ESG context, only Brandstetter and Lehner (2015) implement the BLM in repurposing the view feature as described in Section 3.9. In Walters (2014) a comprehensive synopsis about the principles, proofs and insights to the BLM is given along with a broad literature review.

The above mentioned reverse optimization, thus the extraction of return estimates as implied by the market, is the conceptual core of the BLM. *Reverse* in this case refers to the common optimization process known from MPT, where return estimates as inputs result in the optimal portfolio weights. This relation is reversed in the BLM. From Expression 4.2 of the above section (see also Appendix A.11), the equilibrium returns as generated by reverse optimization deduced from the

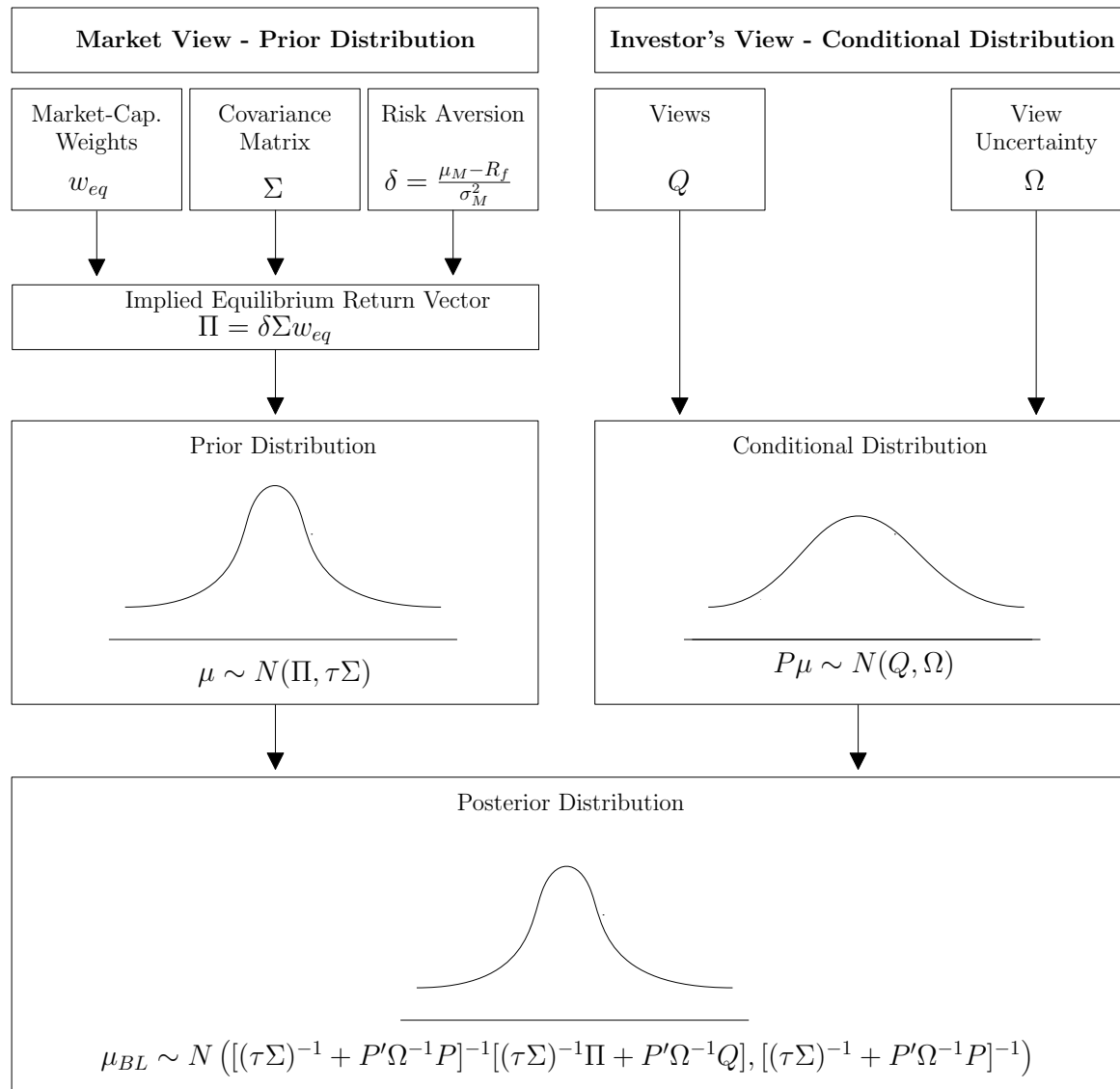


Figure 4.1 – This illustration shows an overview of the inputs and distributions of the BLM. The prior return distribution on the left hand side reflects the market view. It originates from the reverse optimization, deducing implied equilibrium returns from the market capitalization weights as described above. As another input, the covariance matrix Σ and the risk aversion parameter are estimated, market weights are observed. On the right hand side the incorporation of the investor's view is pictured. Defining the view vector Q and the view uncertainty Ω determines the conditional distribution. Blending both distributions results in the BLM-distribution that is then used as input to a normal MV optimizer. (Source: own figure based on Idzorek (2002))

CAPM equilibrium read as

$$(\boldsymbol{\mu} - R_f \mathbf{1}) = \frac{(\mu_M - R_f)}{\sigma_M^2} \Sigma \mathbf{w}_M. \quad (4.3)$$

In the quasi canonical notation prevalent in the BLM literature this is translated into

$$\boldsymbol{\Pi} = \delta \Sigma \mathbf{w}_{eq} \quad (4.4)$$

where in the N asset case, $\boldsymbol{\Pi} = \boldsymbol{\mu} - R_f \mathbf{1}$ is a $(N \times 1)$ vector of equilibrium risk premia, $\delta = \frac{(\mu_M - R_f)}{\sigma_M^2}$ is a scalar and treated as the market average risk aversion parameter, Σ is the $(N \times N)$ covariance matrix and \mathbf{w}_{eq} is the $(N \times 1)$ vector of equilibrium weights given by the market capitalization at the beginning of the period.

The fact that the notation deviates from the one known from CAPM or MPT stems from the conceptual difference of how the expected returns are modeled. In the reference model expected returns r are assumed to be normally distributed:

$$r \sim N(\boldsymbol{\mu}, \Sigma) \quad (4.5)$$

where $\boldsymbol{\mu}$ is the mean and Σ the variance. In the canonical BLM the unknown $\boldsymbol{\mu}$ itself is defined as random variable being normally distributed around the estimate of the mean $\boldsymbol{\Pi}$ and its variance Σ_{Π} :

$$\boldsymbol{\mu} \sim N(\boldsymbol{\Pi}, \Sigma_{\Pi}), \quad (4.6)$$

This is equivalent to state that $\boldsymbol{\mu} = \boldsymbol{\Pi} + \boldsymbol{\epsilon}$, where $\boldsymbol{\epsilon}$ is the deviation of the estimate from the true return and is normally distributed, $\boldsymbol{\epsilon} \sim N(0, \Sigma_{\Pi})$. If additionally it is assumed that $\boldsymbol{\epsilon}$ is uncorrelated with $\boldsymbol{\mu}$, and Σ_r is defined as the variance of returns about the estimate $\boldsymbol{\Pi}$, it must hold that $\Sigma_r = \Sigma + \Sigma_{\Pi}$. Hence, if the estimate gets worse, Σ_{Π} increases and therefore Σ_r alike (Walters, 2014). Thus, the canonical BLM models expected return as

$$r \sim N(\boldsymbol{\Pi}, \Sigma_r). \quad (4.7)$$

Note that the covariance matrix is assumed to be known from the equilibrium conception. In practice, however, it is usually estimated from historical return data (Walters, 2014). Black and Litterman make the assumption that the prior distribution covariance structure is proportional to the covariance of returns. That is, referring to expression 4.6, Σ_{Π} is equal to $\tau \Sigma$, which turns the distribution of prior returns of expression 4.7 into $r \sim N(\boldsymbol{\Pi}, (1 + \tau) \Sigma)$. The factor τ is discussed controversially and set differently in different publications. It reaches in literature from *close to zero* up to *one*. Some

model variations even forgo the use of this parameter. Conceptually, τ carries information about the uncertainty of the investors in their prior estimates of expected returns, i.e. the returns deducted from the CAPM equilibrium (Walters et al., 2013). It is reasoned in Walters et al. (2013) that if the canonical model mentioned above is applied, thus μ is considered a random variable, the factor τ must be defined and calibrated. Yet, since it is a measure for the confidence in the prior estimates, τ remains subjective. Often it is considered in relation to the sample size and τ is set to the maximum likelihood estimator $\frac{1}{T}$ with T being the number of periods used to sample the covariance matrix. This logic treats Π as if it were the result of a regression causing the variance of the estimate Π to be inversely proportional to the sample size T . A very intuitive approach to conceptualize τ is to install it as determinant of confidence intervals for μ . Such a confidence interval could be formally expressed as $\mu \in (\mu \pm z\sqrt{\tau\sigma^2})$, with z being a standardized factor determining the confidence interval, given a normal distribution. Following this argumentation it is obvious that choosing τ too high returns imprecise statements about the estimate (Walters, 2014).³²

4.1.3 Definition of Views

The expected return vector Π and the covariance matrix Σ being the main determinants of the prior distribution, are the minimal inputs required for a typical MV optimizer. Yet, one of the main features of the BLM is the formulation of the additional view inputs. If no views are defined and all other model components remain unchanged, by construction the MV optimization process results in weights proportional to the market portfolio.³³ In the standard BLM views are defined either in absolute statements about the expected return of a single asset or formulated relative to other assets. The second formulation is more common in practice (Idzorek, 2002). A minimal example of how views are expressed in the BLM consider the following $K = 3$ views in an asset universe of $N = 4$ titles, A, B, C, D . An investor is assumed to have the following three views: (i) the expected return of asset B is 3% (absolute view); (ii) asset C is going to outperform asset D by 2.5% in the

³² For numeric examples see Walters et al. (2013) or Zuber (2012).

³³ In fact, it is - not as stated in some publications - not exactly the market portfolio as known from the CAPM; this depends also on the factor τ that specifies the view uncertainty being discussed below in this section. Since the covariance matrix Σ from Expression 4.4 is assumed to be $(1 + \tau)\Sigma$ due to uncertainty about the estimates, the efficient frontier can be thought of being shifted to the right. Or alternatively the no-view investor invests $\frac{1}{1+\tau}$ into the market portfolio and $\frac{\tau}{1+\tau}$ into the risk free asset (see Walters (2014) for further explanations.)

next period (relative view); (iii) an equally weighted portfolio of assets A and B will outperform and equally weighted portfolio of assets C and D by 2%. In the black litterman model this view is represented by defining the $(K \times N)$ link matrix P and the $(K \times 1)$ view vector Q :

$$P = \begin{pmatrix} & A & B & C & D \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & -1 \\ 0.5 & 0.5 & -0.5 & -0.5 \end{pmatrix}, Q = \begin{pmatrix} 0.03 \\ 0.025 \\ 0.02 \end{pmatrix} \quad (4.8)$$

These exemplary chosen views reveal a set of rules applied when defining views: for relative views the positive and negative weights must sum to 1 and -1 respectively, absolute views are attributed a weight of 1. There are also approaches imposing more restrictions on the weights defined in P , e.g. Idzorek (2002) or He and Litterman (2002) define weights in relation to the market capitalization of the involved titles. Intuitively, the relation between P and Q can be described as the potentially underdetermined system of equations $P\mu \approx Q$, with μ as the unknown $(N \times 1)$ vector of expected returns (the approximate equality origins from the involved uncertainty). This system of equations imposes restrictions on the posterior BLM return vector (see also Figure 4.1). Defining views this way is rather flexible, even conflicting views are technically feasible. The mentioned uncertainty is another component determined by the investor and completes the view input. To effectuate a strict equality, the relation between P and Q may be expressed by $P\mu = Q + \epsilon_v$, with ϵ_v being the normally distributed error term $\epsilon_v \sim N(0, \Omega)$ that is assumed to be uncorrelated with the ϵ terms as in the deviations of Π from μ mentioned above. This makes $P\mu$ also normally distributed, i.e. $P\mu \sim N(Q, \Omega)$. As views are assumed to be independent and uncorrelated, Ω is per definition a $(K \times K)$ matrix with off-diagonal elements equal to zero and the diagonal elements ω_{kk} for $k = (1, \dots, K)$ non-zero if a view is expressed, zero otherwise. Analogously to the τ factor, there are different ways to quantify Ω , representing the investor's uncertainty about the views. Similar to the interpretation of τ , it may be useful to treat Ω as determinant of confidence intervals (Mankert, 2006). For example if an investor expresses the k th view that asset A will outperform asset B by 6%, and the confidence is set to 95%, this projection falls within an interval of $[5\%, 7\%]$, the corresponding ω_{kk} would be set to $(0.5\%)^2$. This stems from the fact that the 95% interval from the normal distribution is defined by

approximately $\pm 2\sigma$, thus in the chosen example $\sigma = 0.5\%$. It is a common approach to set the view uncertainty matrix proportional to the prior covariance matrix (He and Litterman, 2002; Meucci, 2010), that is

$$\Omega = \text{diag}(P(\tau\Sigma)P') \quad (4.9)$$

where *diag* is an operator setting off-diagonal elements a square matrix equal to zero. If Ω is defined this way, the uncertainty about the prior and the one about views are equivalent. There are some other ways to specify this model component, a thorough review of most approaches is given in Walters (2014).

4.1.4 Blending the Market Portfolio with Investor Views

There are different ways of combining the equilibrium with the investor's views within the BLM framework. This thesis follows the Bayesian approach. Consequently and according to Bayesian statistics, the notion of probability is understood as a degree of belief that is updated once new information is obtained. From a Bayesian perspective and applying probability density functions (PDF), the posterior probability can be stated as follows:

$$\text{pdf}(\mu | \Pi) = \frac{\text{pdf}(\Pi | \mu) \times \text{pdf}(\mu)}{\text{pdf}(\Pi)} \quad (4.10)$$

where $\text{pdf}(\mu | \Pi)$ is the PDF of the posterior probability distribution, i.e. the updated probability of μ given the observed market equilibrium returns Π , $\text{pdf}(\Pi | \mu)$ is the PDF of the *conditional probability* distribution of Π given μ , $\text{pdf}(\mu)$ and $\text{pdf}(\Pi)$ are the PDFs of the *unconditional* probability distributions of μ and Π . Assuming normally distributed returns, Expression 4.10 is the starting point to deduce the posterior distribution that is multivariate normal and specified by the mean

$$\mu_p = [(\tau\Sigma)^{-1} + P'\Omega^{-1}P]^{-1}[(\tau\Sigma)^{-1}\Pi + P'\Omega^{-1}Q] \quad (4.11)$$

and the covariance matrix

$$\Sigma_p = [(\tau\Sigma)^{-1} + P'\Omega^{-1}P]^{-1} \quad (4.12)$$

which defines the posterior distribution of the BLM (compare also Figure 4.1) as:

$$\mu_{BL} \sim N \left([(\tau\Sigma)^{-1} + P'\Omega^{-1}P]^{-1}[(\tau\Sigma)^{-1}\Pi + P'\Omega^{-1}Q], [(\tau\Sigma)^{-1} + P'\Omega^{-1}P]^{-1} \right). \quad (4.13)$$

This expression is sometimes referred to as the Black Litterman master formula. A thorough and

commented derivation thereof is given in Appendix B.4.

The covariance matrix Σ_P might be mistaken to describe the variance of the returns, yet Σ_P quantifies the variance of the posterior mean estimate about the actual mean (Walters, 2014). Following He and Litterman (2002) and Walters (2014), it is not consistent to optimize a portfolio based on Σ_P only, rather it is required to add Σ_P , representing uncertainty about the estimates, to the variance from the distribution about the return estimates Σ . That is, the input covariance matrix to the MV optimization process becomes

$$\bar{\Sigma} = \Sigma_P + \Sigma \quad (4.14)$$

which after substituting the posterior variance leads to

$$\bar{\Sigma} = [(\tau\Sigma)^{-1} + P'\Omega^{-1}P]^{-1} + \Sigma. \quad (4.15)$$

Equation 4.15 clarifies that in the absence of views, $\bar{\Sigma}$ becomes $(1 + \tau)\Sigma$, hence assuming $\tau > 0$, the variance of the estimated returns will be greater than the one of the prior distribution.

Assuming that the investor defines a view on a subset of assets, the effect of the posterior estimate of the variance $\bar{\Sigma}$ is intuitive. Covariance entries with low variances, that is with a higher degree of precision of the estimated mean, will be favored as compared to such with high variances and the portfolio weights will be tilt accordingly.

Analyzing the components in Expression 4.11 it is obvious that μ_P is a weighted average of the expected market returns and the ones coming from the investor's views. The left limb of the formula, $[(\tau\Sigma)^{-1} + P'\Omega^{-1}P]^{-1}$, acts as a normalizing component. The intuition behind this becomes evident when $\tau\Sigma$ and Ω are considered as measures of uncertainty, which turns their respective inverse into a quantification of confidence in the expected returns (Cheung, 2010).

Having defined μ_P and $\bar{\Sigma}$, the resulting maximization problem is denoted as

$$\arg \max_w U(\mu_P, \bar{\Sigma}) = \mathbf{w}'\boldsymbol{\mu}_P - \frac{\delta}{2}\mathbf{w}'\bar{\Sigma}\mathbf{w} \quad (4.16)$$

with δ being the average risk parameter of the market. The maximization of this quadratic utility function leads to the first order condition $\boldsymbol{\mu}_P = \delta\bar{\Sigma}\mathbf{w}^*$ or accordingly to

$$\mathbf{w}^* = \frac{1}{\delta}\bar{\Sigma}^{-1}\boldsymbol{\mu}_P \quad (4.17)$$

with \mathbf{w}^* being the optimal portfolio weights. When no views are defined ($\bar{\Sigma} = (1 + \tau)\Sigma$), it can now

easily be shown, that since the BLM investor is uncertain about the CAPM equilibrium weights, she invests in a fraction of the market portfolio (He and Litterman, 2002), or formally:

$$\frac{\mathbf{w}^*}{1 + \tau} = \frac{1}{\delta} \Sigma^{-1} \boldsymbol{\mu}_P. \quad (4.18)$$

This concludes the basic ingredients of the BLM. In the next section the incorporation of ESG based on the BLM is elaborated.

4.2 Modification of the BLM towards Inclusion of ESG Measures

The approaches towards quantitative inclusion of ESG considerations into portfolio management portrayed thus far in Chapter 3 tend to exhibit an increased level of complexity as compared to the investment process of a typical MV orientated investor and hence might forfeit practicability and attractiveness to a certain degree. The BLM based method proposed in this section aims at overcoming this gap. The method accounts for practicability in featuring the following characteristics with the purpose to overcome some of the barriers to incorporating ESG criteria in mainly institutional portfolio management:

- (i) Allowing for benchmark orientation.
- (ii) Remaining in the two dimensional MV criterion space to overcome the concerns about fiduciary duty.
- (iii) Possibility of moderate weight shifting according to ESG criteria.
- (iv) Possibility to modify / customize ESG incorporation in intensity and nature.
- (v) Maintaining portfolio diversification while accounting for ESG criteria.
- (vi) Linking a rewarding/penalizing functionality to ESG scores, such that resulting portfolios perform better than (or at least as good as) the benchmark in terms of ESG.
- (vii) Maintaining the capability of the BLM for the informed investor to express views.
- (viii) Maintaining portfolio weight stability in a multiperiod rebalancing procedure.

The core idea of the proposed method is to impose a structure on the covariance matrix by means of the modification of the variance terms. This modified covariance matrix is then used

as input parameter in a conventional MV-optimization process.³⁴ The covariance matrix, just like the expected returns, is an estimate and in the BLM literature it is mostly based on historical sample covariance matrices.³⁵ The rationale of the developed method lies in the assumption of ESG measures to add informational value to the model input *variance* reflecting idiosyncratic risk of the single assets in the model. That is, if ESG factors are assumed to bare predictive information about a company's risk, it is reasonable to include this information in forming the expectation about portfolio variance. Here, the assumption of the CAPM of non-systematic risk not being compensated for as it is diversifiable, is essentially relaxed when applying this method. This can be rationalized if markets are assumed to be not fully efficient (see e.g. Dumas et al. (2015)). Also, if the number of titles in the portfolio is limited, as for example it is the case in the empirical test of the method in Chapter 5, it is reasonable to modify variance terms. Formally, this can be illustrated in the portfolio variance expression for an equally weighted portfolio derived in Appendix A.3:

$$\sigma_{PF}^2 = \frac{1}{n} \tilde{\Sigma}^2 + \frac{n-1}{n} \tilde{\sigma}_{i,j} \quad (4.19)$$

with $\tilde{\sigma}^2$ and $\tilde{\sigma}_{i,j}$ being the average portfolio variance and covariance. This illustrative expression of the portfolio variance shows the diversification effect, as n tends to infinity the variance terms converge towards zero and the covariance terms towards the average covariance. However, for numerous indices n is in a range where single variances matter in terms of contribution to the portfolio variance. Moreover, the majority of indices allow for differences in portfolio weights, such that the variances of higher weighted titles potentially contribute quite considerably to the portfolio variance.

There are two main elements of covariance matrix modification as compared to the standard BLM: (i) A shrinkage method proposed by Ledoit and Wolf (2003) to mitigate the effects of estimation errors linked to the use of sample covariance matrices based on historical returns. This modification lowers extreme values of the covariance matrix in a statistically consistent way, yet is not directly linked to the incorporation of ESG factors. The shrinkage precedes the modification of the variances, i.e. the shrunk covariance matrix replaces the sample covariance matrix and is an input to generate the posterior BLM covariance matrix $\bar{\Sigma}$.³⁶ A short description of the principle of the applied shrinking

³⁴ A similar method was developed in Zuber (2012), yet in the context of behavioral finance, in particular considering the Prospect Theory (Kahneman and Tversky, 1979).

³⁵ The application of historical sample assures the covariance matrices to be positive definite (see also Walters (2014)).

³⁶ This is different from Zuber (2012), where the variance modification and shrinking part are combined in one step.

method is given in Appendix A.12. (ii) The modification of the variance terms of $\bar{\Sigma}$ to alter the resulting portfolio weights according to some ESG score, which is shown in the next paragraphs.

For a thorough understanding of how the modification of variances works, it is useful to reconsider Expression 4.17 from the above section, determining the resulting (unconstrained) optimal weights in the BLM process:

$$\mathbf{w}^* = \frac{1}{\delta} \bar{\Sigma}^{-1} \boldsymbol{\mu}_P. \quad (4.20)$$

Thus, the weight vector is mainly determined by the expected return vector $\boldsymbol{\mu}_P$, the average risk aversion coefficient from the market δ , and the inverse of the posterior covariance matrix $\bar{\Sigma}$. The equation reveals that assets with large expected returns and a low contribution to the portfolio variance tend to be overweighted and vice versa. In a standard MV setup, concerning the sensitivity of the portfolio weights to changes of the inputs, adjustments of the expected returns weigh more than adjustments in the covariance matrix, and changes to the variance terms weigh more than changes to the covariance terms (Best and Grauer, 1991; Fabozzi et al., 2007).³⁷ Yet, by construction the BLM mitigates this sensitivity and so does also the application of covariance shrinking mentioned above. These preconditions allow for moderate portfolio weight shifting caused by variation of the inputs. The concept of modeling variance terms is already applied within the BLM framework, the diagonal matrix Ω expresses uncertainty about the investors views modifying the variance terms coming from return covariance estimation accordingly. While this procedure only alters variances of assets that actually the investor defines a view for, the proposed method (henceforth referred to as Adjusted Variance Method (AVM)) virtually tackles the variance terms of every asset.

Formally, the modified covariance matrix Γ with the entries γ_{ij} for $i, j = 1, \dots, N$ can be expressed as follows

$$\Gamma = \bar{\Sigma}_S \circ A^{\circ\kappa} \quad (4.21)$$

with $\bar{\Sigma}_S$ as the posterior BLM covariance matrix based on the shrunk sample covariance matrix, the entries of which are $\bar{\sigma}_{S_{ij}}$ for $i, j = 1, \dots, N$, and A as the matrix of adjustment-entries a_{ii} (further specification of these factors is given below) and the off-diagonal entries $a_{ij} = 1$, where $i \neq j$. The

³⁷ According to Fabozzi et al. (2007) as a rule of thumb changes in returns weigh ten times more than changes in the covariance matrix, and changes in the variance terms thereof weigh twice as much as changes in covariance terms. This holds for plain MV optimization and the elasticity is also a function of the number of titles in the portfolio and the risk aversion coefficient.

latter assures that the covariances remain unchanged. The exponent $\kappa \geq 0$ quantifies the adjustable intensity of ESG incorporation; when $\kappa \in [0, 1]$ the ESG inclusion reaches from no variance modification at all ($\kappa = 0$) to a straight one-to-one effect ($\kappa = 1$), if $\kappa > 1$ the effect gets more pronounced.³⁸

The \circ -operator represents a Hadamard operation, thus an element-wise matrix operation for multiplication as well as exponentiation. Consequently, single entries of Γ are expressed as $\gamma_{ij} = \bar{\sigma}_{S_{ij}} a_{ij}^\kappa$.

Algebraically, matrix A may be generated as $A = J - I + (\text{diag}(\mathbf{a}))$ where J is a $N \times N$ matrix of ones, I is the $N \times N$ identity matrix, $\text{diag}(\mathbf{a})$ is a diagonalized $1 \times N$ vector of adjustment factors.

Written in matrix notation this becomes:

$$\begin{pmatrix} a_{11} & 1 & \dots & 1 \\ 1 & a_{22} & \dots & 1 \\ \vdots & \vdots & \ddots & \vdots \\ 1 & 1 & \dots & a_{nn} \end{pmatrix} = \begin{pmatrix} 1 & 1 & \dots & 1 \\ 1 & 1 & \dots & 1 \\ \vdots & \vdots & \ddots & \vdots \\ 1 & 1 & \dots & 1 \end{pmatrix} - \begin{pmatrix} 1 & 0 & \dots & 0 \\ 0 & 1 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & 1 \end{pmatrix} + \begin{pmatrix} a_{11} & 0 & \dots & 0 \\ 0 & a_{22} & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & a_{nn} \end{pmatrix} \quad (4.22)$$

Accordingly Expression 4.21 can be expressed as

$$\begin{pmatrix} a_{11} * \bar{\sigma}_{S_{11}} & \bar{\sigma}_{S_{12}} & \dots & \bar{\sigma}_{S_{1n}} \\ \bar{\sigma}_{S_{21}} & a_{22} * \bar{\sigma}_{S_{22}} & \dots & \bar{\sigma}_{S_{2n}} \\ \vdots & \vdots & \ddots & \vdots \\ \bar{\sigma}_{S_{n1}} & \dots & \dots & a_{nn} * \bar{\sigma}_{S_{nn}} \end{pmatrix} = \begin{pmatrix} \bar{\sigma}_{S_{11}} & \bar{\sigma}_{S_{12}} & \dots & \bar{\sigma}_{S_{1n}} \\ \bar{\sigma}_{S_{21}} & \bar{\sigma}_{S_{22}} & \dots & \bar{\sigma}_{S_{2n}} \\ \vdots & \vdots & \ddots & \vdots \\ \bar{\sigma}_{S_{n1}} & \dots & \dots & \bar{\sigma}_{S_{nn}} \end{pmatrix} \circ \begin{pmatrix} a_{11} & 1 & \dots & 1 \\ 1 & a_{22} & \dots & 1 \\ \vdots & \vdots & \ddots & \vdots \\ 1 & 1 & \dots & a_{nn} \end{pmatrix}^{\circ\kappa}$$

To compute the final portfolio weights, the resulting covariance matrix Γ together with the posterior expected return vector $\boldsymbol{\mu}_P$ are used as inputs to a common MV optimizer under no short-selling-constraints and the full-allocation constraint (weights required to sum to unity). When no constraints are applied, the closed form solution can be expressed formally as

$$\begin{aligned} \mathbf{w}^* &= \frac{1}{\delta} \Gamma^{-1} \boldsymbol{\mu}_P \\ &= \frac{1}{\delta} (\bar{\Sigma}_S \circ A^{\circ\kappa})^{-1} \boldsymbol{\mu}_P. \end{aligned} \quad (4.23)$$

In the empirical chapter below, constraints are active and a computational non-linear programming solver is applied.

³⁸ Yet, to get meaningful results κ should be raised only moderately, see also Chapter 5.

To ensure that the modifying elements of the A matrix relate to ESG, there are potentially numerous ways to specify a_{ii} entries and there is not a single right method. Subsequently, two main approaches are suggested.

In a *direct* approach, the variance terms of the posterior covariance matrix $\bar{\Sigma}_S$ are assumed to neglect completely the risk dimension carried by ESG measures. That is, to account for ESG considerations the variance terms are multiplied by $a_{ii} \geq 1$. When ESG scores $\in [0, 1]$ are applied, as it is the case in the empirical implementation of the method in Chapter 5, with 0 being the lowest (worst) and 1 highest (best) ESG score, one way to reflect the risk information is to define

$$a_{ii} = 2 - ESG_{ii} \quad (4.24)$$

where ESG_{ii} is the ESG score of asset i . That is, a hypothetically perfect asset i in terms of ESG considerations is attributed an ESG score of 1, thus by the fact that $a_{ii} = 2 - 1 = 1$, the corresponding variance term is not penalized. However, most assets are not considered as perfect ESG wise, thus the adjustment factor a_{ii} will take values greater than one for virtually any asset; it will be close to 1 for the best ESG companies and close to 2 for poor ESG performers. With a maximal penalization of 2 and the intensity $\kappa \in [0, 1]$ moderate weight shifting is favored. According to this logic, any variance-term is penalized, yet some more than others, hence the portfolio weights of good ESG companies tend to increase and vice versa. It is important to notice that this holds true as a tendency and not as an absolute statement, more on that issue below in this section.

An alternative *indirect* approach that is suggested to quantify the diagonal entries of the adjustment matrix A is an internal benchmarking approach according to which the weights are modified due to the ESG score relative to the other portfolio members' scores. Obvious choices for the benchmark are the sample-mean or the median, both being representations for the center of covered ESG data. Accordingly and with M being a generic variable for either the arithmetic sample mean or the median describing the sample of the portfolio members' ESG scores at time t , the diagonal A entries are expressed as³⁹

$$a_{ii} = \frac{M}{ESG_{ii}} \quad , \text{ for } ESG_{ii} \neq 0. \quad (4.25)$$

³⁹ Here, the assumption of $ESG_{ii} \neq 0$ is formally necessary and practically reasonable.

Hence, $a_{ii} = 1$ if the ESG score of title i is exactly equal to M , such that the variance is neither penalized nor rewarded; $a_{ii} < 1$ if $ESG_{ii} > M$. That is, if in terms of ESG a title performs superior as compared to the mean or median score of the portfolio, the variance term of asset i is lowered (rewarded), if it is inferior it is penalized (raised). As for the *direct* method, this shifts portfolio weights accordingly. While the mean is potentially prone to outliers, the median is likely to produce more robust adjustments, which is caused by dividing the sample of assets in titles that are rewarded and titles that are penalized more or less in equal parts (depending on whether N is even or odd). Generally, as the adjustment factors of the indirect approach are allowed to exceed a doubling, the weight shifting of the indirect approaches are likely to be more distinct as compared to the direct approach.

In the above paragraphs it is mentioned that superior ESG scores *tend* to lead to increased portfolio weights. However this cannot be taken as a rule for neither of the approaches. This reasoning originates from the fact that there are other determinants of portfolio weights like the covariance terms, the magnitude of the variances and covariances, the sign of the covariances, the expected returns and the dispersion of the adjustment terms a_{ii} . Also, there are typically numerous titles in the portfolio that contribute to the portfolio variance, the weights of which are altered, too, due to their ESG scores. This implies that an asset with good ESG scores not necessarily gains portfolio weight as compared to the non ESG consideration case or even as compared to a title with a - considered in isolation - inferior ESG score. Thus, on the single asset level it is even possible that a security with a lower ESG score gains weight in the resulting portfolio, while the higher ESG score title weight decreases. To follow this logic it is useful to think of a hypothetical portfolio of two assets being identical in their specifications except from their variance terms, say asset 1 has a variance of $\bar{\sigma}_{11} = 0.05$, asset 2 one of $\bar{\sigma}_{22} = 0.01$. Clearly, a MV optimization attributes a weight of 1.0 to asset 2 (as also their covariance terms are equal by definition). Now, assume asset 1 is attributed the maximal ESG score of 1.0 and asset 2 the minimal score of 0.0. In fact, applying the direct method leads to the modified variance terms $\gamma_{11} = a_{11} \times \bar{\sigma}_{11} = (2 - 1) \times 0.05 = 0.05$ and $\gamma_{22} = a_{22} \times \bar{\sigma}_{22} = (2 - 0) \times 0.01 = 0.02$. As the penalization factor in this case is too small, still the resulting portfolio will only contain asset 2, despite it exhibits a maximally inferior ESG score as compared to asset 1. Contrary to this, both indirect methods (assuming an ESG score converging to

zero for asset 2) lead to the exact opposite result, since the rewarding/penalizing measures are now $a_{11} = \frac{M}{ESG_1} \approx 0.5$ and $a_{22} = \frac{M}{ESG_2} \approx \infty$, thus the portfolio will only contain asset 1. This thought experiment is illustrative and is supposed to clarify the effects of the methods. However, *ceteris paribus* the weight of asset i exhibiting an increased ESG score will at least be equal or greater compared to the original portfolio. This reasoning is founded in the MV optimization that aims at maximizing the (ex ante) Sharpe Ratio of the portfolio. The contribution to the latter coming from asset i is more favorable as compared to the original portfolio since its variance is decreased by the application of the method. The same reasoning of a modified contribution to the portfolio Sharpe Ratio for all portfolio members according to their relative ESG performance ensures that the overall portfolio ESG score will increase (or at least remain the same) as compared to the non ESG consideration case. The most intuitive way to consider the incorporation of ESG scores is to deem them an additional criterion altering the risk-return characteristics within the portfolio optimization process.

In general, neither of the approaches disrupts the positive definiteness of the covariance matrix, since the only altered values are variances, that are greater than zero by definition (given risky assets) and also the entries of the A -matrix are strictly positive in any case. Moreover, according to the Schur Product Theorem the Hadamard Product of two positive definite matrices is again positive definite (Schur, 1911).

Furthermore, both approaches that are discussed may be enriched with additional constraints that are commonly used in portfolio optimization, as e.g. weight limits, but also a minimal ESG portfolio score constraint. Moreover, there may be different approaches to restructure the covariance matrix, yet the present thesis focuses on providing a basic implementation of the model.

Empirical Application

In this chapter the AVM with its different approaches is implemented with altering parameter values and the resulting portfolios are analyzed regarding the effects of ESG inclusion to portfolio construction and out-of-sample performance. The description of used data is given in Section 5.1, the empirical analysis in Section 5.2.

5.1 Data Description

The market in consideration is the Swiss stock market being represented by the Swiss Market Index (SMI), which is a market capitalization weighted price index of the 20 most capitalized and liquid stocks of the Swiss Performance Index (SPI) (SIX, 2016).⁴⁰ The index constituents used for the empirical analysis correspond to the actual constituents by April 2016 excluding *Actelion* and *Bank Julius Baer* due to incomplete data; this diminished SMI will be referred to as the SMI(-). The complete list and the corresponding weights as of December 2014 of the 18 SMI(-) constituents is given in Table D.2 in Appendix D. The SMI as a Swiss bluechip index is suitable for testing the method due to its modest number of titles and also the heterogeneity of weights with few index heavyweights and some less represented stocks. Also, bluechip titles are more likely to be attributed ESG scores from data providers. The time-frame in scope is January 31, 2002 up to December 31, 2014, hence 156 monthly price observations in (Swiss Francs) or 155 monthly return observations for

⁴⁰ Data source for asset prices is Thomson Reuters Datastream, a subscription service portal.

each of the assets. It is important to note that the financial crisis 2007-2008 is included in the period of consideration. Although performance measures as to be found in Section 5.2 can be calculated for a post financial crisis period, the latter still influences the results via the estimated covariance matrices.⁴¹ The single period net return of asset i for period t is calculated arithmetically, thus $r_{i,t} = \frac{S_{i,t} - S_{i,t-1}}{S_{i,t-1}}$ with S_i being the price of stock i . The riskfree rate is approximated by monthly observations of the 3-month LIBOR (London Interbank Offered Rate), data was retrieved from the Swiss National Bank (SNB, 2016).

As for the exogenous BLM parameters, the average market risk aversion parameter was set to $\delta = 2.75$, which is based on a longterm empirical average and corresponding to the BLM literature consensus with δ values between 2 and 3. The uncertainty factor about the prior estimate τ is set to 0.05 in accordance with He and Litterman (2002). Moreover, the view uncertainty matrix is computed as $\Omega = \text{diag}(P(\tau\Sigma_S)P')$, see also Section 4.1.

ESG scores were retrieved from the Thomson Reuters *Asset4* database featuring the categories *Environmental*, *Social*, *Corporate Governance* and *Economic*, spanning 500 datapoints in total to cover more than 180 key performance indicators for ESG. For the provider's description of the categories see Table D.3 in Appendix D. The original scores' range lies within an interval $[0, 100]$, for the use in the AVM it was scaled to $[0, 1]$. The titles of the SMI perform relatively well as measured by this score; the majority of the securities are centered in the top quintile⁴² in terms of overall ESG score, see the boxplots in Appendix C.5. Four remarks on the use of these measures: (i) ESG scores are highly condensed measures and it is arguable whether they do justice to a fair representation of a company's ESG performance. (ii) For the sake of the empirical analysis the *equally weighted* score over all four categories given by the database is applied.⁴³ (iii) The applied ESG scores are only updated on a yearly basis. For the practical implementation of the model, it might make sense to update ESG scores on a higher frequency level, e.g. after the occurrence of new relevant information. (iv) ESG scores are compositions of publicly available data (e.g. sustainability reports or information on the corporate websites) and may be biased.

⁴¹ Correlations during crisis are usually stronger than in average times see e.g. Sandoval and Franca (2012).

⁴² Quintile refers to the ESG scores of the worldwide asset sample population as covered by the Asset4 database.

⁴³ A quick check revealed that the term *equally weighted* may be misleading, since the weights are not quite equal. Yet, they are rather balanced.

5.2 Empirical Analysis

As the main goal of the proposed method is to account for ESG scores while still focusing on a benchmark index, the effects of the method to portfolio weights is studied in the first place. Based on the shrunk sample covariance matrix that is computed on the basis of single asset returns from the preceding five years and with no investor views defined, optimal weights according to the different approaches proposed in Section 4.2 are generated. The exponent κ as the investor defined measure of degree of ESG incorporation is set to 1 when nothing else is indicated. A static observation of the corresponding weights as of January 2007 is given in Table 5.1.

	ESG	w_{BLM}^*	w_D^*	Δ_D	a_{ii}	w_{I1}^*	Δ_{I1}	a_{ii}	w_{I2}^*	Δ_{I2}	a_{ii}
NES	0.9377	0.1632	0.1632	-0.0000	1.0623	0.1879	0.0248	0.8489	0.1767	0.0135	0.9482
NOV	0.8989	0.1674	0.1568	-0.0106	1.1011	0.1689	0.0014	0.8855	0.1633	-0.0041	0.9891
ROC	0.9282	0.1465	0.1444	-0.0021	1.0718	0.1649	0.0184	0.8576	0.1556	0.0090	0.9579
UBS	0.9421	0.1462	0.1460	-0.0001	1.0579	0.1848	0.0387	0.8449	0.1644	0.0182	0.9437
ABB	0.9542	0.0428	0.0425	-0.0003	1.0458	0.0532	0.0103	0.8342	0.0476	0.0048	0.9318
SYN	0.9268	0.0213	0.0292	0.0079	1.0732	0.0156	-0.0057	0.8589	0.0244	0.0031	0.9593
CS	0.8881	0.0952	0.0865	-0.0087	1.1119	0.1005	0.0054	0.8963	0.0929	-0.0022	1.0011
SRE	0.9441	0.0346	0.0410	0.0064	1.0559	0.0377	0.0032	0.8431	0.0406	0.0061	0.9417
RIC	0.8901	0.0323	0.0350	0.0027	1.1099	0.0265	-0.0058	0.8943	0.0323	-0.0000	0.9989
ZUR	0.6258	0.0432	0.0303	-0.0128	1.3742	0.0226	-0.0206	1.2720	0.0242	-0.0190	1.4207
LAF	0.9537	0.0278	0.0356	0.0078	1.0463	0.0120	-0.0158	0.8346	0.0273	-0.0005	0.9323
SCM	0.6853	0.0235	0.0237	0.0002	1.3147	0.0139	-0.0096	1.1615	0.0187	-0.0048	1.2974
GIV	0.7627	0.0072	0.0106	0.0034	1.2373	0.0000	-0.0072	1.0437	0.0017	-0.0056	1.1657
SGS	0.4083	0.0095	0.0099	0.0004	1.5917	0.0021	-0.0074	1.9495	0.0045	-0.0050	2.1776
SLI	0.6475	0.0094	0.0089	-0.0006	1.3525	0.0017	-0.0078	1.2293	0.0052	-0.0042	1.3731
GEB	0.8250	0.0078	0.0118	0.0040	1.1750	0.0000	-0.0078	0.9648	0.0063	-0.0015	1.0777
ADE	0.8520	0.0134	0.0159	0.0024	1.1480	0.0075	-0.0060	0.9343	0.0126	-0.0008	1.0435
SWA	0.2575	0.0085	0.0086	0.0001	1.7425	0.0000	-0.0085	3.0913	0.0018	-0.0068	3.4528
ESG_{PF}	-	0.8891	0.8924	-	-	0.9125	-	-	0.9063	-	-

Table 5.1 – This Table shows static observations of the effects after applying the AVM as of January 2007, the first three columns being the company names, ESG scores and market weights. The latter corresponds to the no-view BLM portfolio. The columns to the right of the market weights are three blocks of the type *optimal weights according to the approach*, w^* , *differences to market weight*, Δ , and the corresponding *A-matrix entries*, a_{ii} . The subscript D stands for the direct method, $I1$ for the indirect method with *mean* as location parameter, and $I2$ for the indirect method based on the distance to the *median*. The entries of the last row correspond to the ESG scores of the according portfolios.

Focusing on the resulting optimal weights w_D^* in table 5.1 generated by the direct version of the AVM, it is apparent that the modified weights for most of the assets diverge from the market weights rather moderately. As by construction the corresponding a_{ii} entries lie in the interval $[1, 2]$, i.e. all variances are penalized, yet to a different degree. As outlined in Section 4.2, it is not obvious to assign a directly observable effect to the application of a_{ii} . This is due to the fact that the ESG score is only one criterion besides the expected return and the variances and covariance-terms. Taking

it into consideration, casually speaking, reshuffles the cards in terms of ex ante portfolio Sharpe Ratio contribution as outlined in section 4.2. The most prominent weight shift in column Δ_D is a drop of 1.28% as compared to the market portfolio for Zurich Insurance (ZUR), which indeed features one of the lowest ESG scores for the considered period. The highest weight increase due to the application of the direct method can be observed for Syngenta (SYN) with 0.79%, and in fact the company is attributed a rather high ESG score. Yet, Swatch (SWA) as the title with the lowest ESG score exhibits virtually no portfolio weight shift at all. The reasons for this are (i) the weight being a function of multiple factors; the contribution to the portfolio Sharpe Ratio is indeed worsened, but not enough relatively to the other factors and titles to evoke a weight change (see also the two asset portfolio reasoning in Section 4.2); (ii) in the sense of market portfolio tracking, the most influential input remains the expected return vector, i.e. the range of deviation of the market portfolio is limited (see also the sensitivity analysis below); (iii) the direct method produces the most modest adjustment measures of all approaches. The overall effect however is positive as indicated by the portfolio ESG score. The two blocks on the right hand side of Table 5.1 show the weight shifting according to the indirect methods with respect to the ESG mean of the portfolio (w_{I1}^*) and the median (w_{I2}^*). It is evident that the weight differentials as compared to the market portfolio are more prominent than for the weights generated by the direct method. The tendency of high ESG score titles gaining weight and low ones being penalized is more accentuated than after the application of the direct method, such that e.g. for UBS the weight surplus amounts to 3.87% and the weight drop for ZUR to 2.06% according to the mean relating approach (column Δ_{I1}). The deviation from the mean ESG score produces a_{ii} -entries that cause highest weight differentials as compared to the other approaches. Accordingly, the overall ESG score of the portfolio is highest for the mean related reward/penalization method. Three relatively poor ESG performers even drop out of the portfolio. The cause for this effect is clarified by considering the reference score; the mean of 0.7960 for this period vs. the ESG median of 0.8891, favors the weight of the top ESG scorers most by construction of the a_{ii} entries. This additional weight for the top ESG titles is shifted from the low ESG performers. Yet, the difference between the effect of the mean and the median approach depends on the data. In particular, values close to the limits of the interval move the mean towards more extreme values. In general, the median method delivers more balanced results, which causes

more moderate weight shifting, as it refers to the center of the data that is less prone to outliers.

As per construction the main determinants of the weights are the expected returns, which is the reason for a certain stickiness to the benchmark weights. In this respect it is interesting to investigate the sensitivity of the resulting weights with respect to ESG scores. To this end, complementing the above analysis, the resulting portfolio weights for a heavy weight (NES) and a light weight (SWA) title are plotted as a function of ESG scores (running from close to zero to one). The result is shown in Figure 5.1.

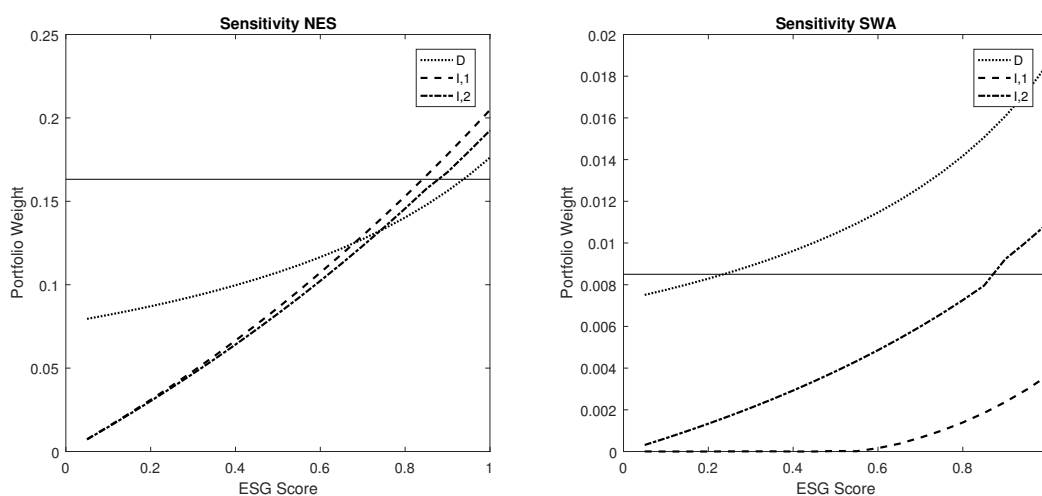


Figure 5.1 – This figure shows the weights of NES and SWA as functions of their ESG scores. The reference situation is the static observation as shown in Table 5.1; mean and median consistently are adjusted according to the change of the respective ESG score. The horizontal line in both cases corresponds to the weights in the unaltered market portfolio. (Source: own figure)

Figure 5.1 clarifies the effects of the three approaches on the corresponding portfolio weights. The direct method (D) has the property of being more balanced in the sense of limiting the deviation from market weights most for index heavyweights like NES and linked to this not neglecting small portfolio weight titles as SWA. This is opposed to the mean referring approach ($I1$) that penalizes the weight of SWA as compared to the market even when its ESG score is maximal. In this case SWA is crowded out by the positive weight shifts of the titles starting already with significant weights. The median referring approach ($I2$) again is less extreme in its outcome. It is also interesting that the penalization imposed by both indirect methods ($I1$ and $I,2$) is able to force the weights to converge to zero when ESG scores tend to the minimum.

To conclude the part of the static empirical analysis, the functionality of defining BLM views is tested, results are presented in Table 5.2. It is obvious that a relatively minor view differential (UBS outperforms CS within a year by 2%) causes rather drastic weight changes. Yet, this is in line with other applications of the BLM with similar BLM inputs to the model, see eg. the implementation of He and Litterman (2002). However, the functionality of the view incorporation alongside ESG corporation is maintained. This meets the expectations since views constitute only another determinant of the weights and their incorporation is straightforward in the sense of the BLM. As the scope of the present thesis is not the formulation of specific views, it is refrained from further analysis in this direction.

	ESG	w_{BLM}^*	w_D^*	Δ_D	w_D^{View}	$\Delta_{D,noView}$	$\Delta_{D,BLM}$
NES	0.9377	0.1632	0.1632	-0.0000	0.1624	-0.0008	-0.0008
NOV	0.8989	0.1674	0.1568	-0.0106	0.1591	0.0022	-0.0084
ROC	0.9282	0.1465	0.1444	-0.0021	0.1420	-0.0024	-0.0045
UBS	0.9421	0.1462	0.1460	-0.0001	0.2603	0.1143	0.1141
ABB	0.9542	0.0428	0.0425	-0.0003	0.0404	-0.0021	-0.0024
SYN	0.9268	0.0213	0.0292	0.0079	0.0257	-0.0034	0.0044
CS	0.8881	0.0952	0.0865	-0.0087	0.0000	-0.0865	-0.0952
SRE	0.9441	0.0346	0.0410	0.0064	0.0363	-0.0047	0.0017
RIC	0.8901	0.0323	0.0350	0.0027	0.0336	-0.0014	0.0012
ZUR	0.6258	0.0432	0.0303	-0.0128	0.0286	-0.0017	-0.0146
LAF	0.9537	0.0278	0.0356	0.0078	0.0310	-0.0046	0.0032
SCM	0.6853	0.0235	0.0237	0.0002	0.0244	0.0007	0.0009
GIV	0.7627	0.0072	0.0106	0.0034	0.0087	-0.0019	0.0015
SGS	0.4083	0.0095	0.0099	0.0004	0.0085	-0.0015	-0.0010
SLI	0.6475	0.0094	0.0089	-0.0006	0.0067	-0.0022	-0.0027
GEB	0.8250	0.0078	0.0118	0.0040	0.0099	-0.0020	0.0021
ADE	0.8520	0.0134	0.0159	0.0024	0.0138	-0.0020	0.0004
SWA	0.2575	0.0085	0.0086	0.0001	0.0086	-0.0001	0.0000

Table 5.2 – This table shows the effect of an investor’s view stating that the UBS will outperform the CS by 2% within a year, which translates input-wise into a monthly excess return of $1.02^{\frac{1}{12}} - 1 = 0.0017$. This view is represented in the Q -vector from the BLM and the corresponding P vector. The first two blocks of the table refer to Table 5.1 for the sake of comparison. The resulting weights after defining views are shown in column w_D^{View} . It can be observed that this leads to CS dropping out of the portfolio while UBS gains 11%. The last two columns quantify the difference of the resulting view generated weights w_D^{View} to w_D^* (no view) and w_{BLM}^* (market) as of January 2007. The comparison of the weights show that the weight changes to the titles excluded from the view are minimal, which indicates that the incorporation of views besides the incorporation of ESG scores is functional.

For an out-of-sample analysis of the portfolios generated by the AVM a monthly rolling window of five years for the covariance matrix and a monthly update of the remaining inputs from January 2007 to December 2014 is considered to compute the inputs in order to monthly rebalance the portfolio.

The time series of monthly rebalancing is shown in Figure 5.2.

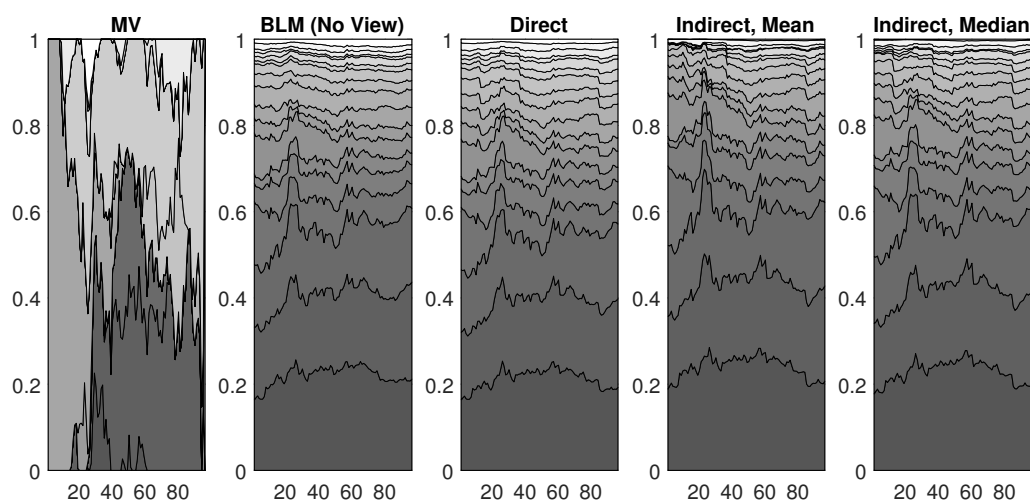


Figure 5.2 – This figure shows the monthly rebalancing of the portfolios. The x-coordinate corresponds to the number of months, the y-coordinate to the portfolio weights. The weights of the titles are stacked; every shade of gray represents one asset. (Source: own figure)

Figure 5.2 demonstrates that the observations made in the static analysis above seem to be persistent over time. That is, the weighting according to the direct AVM method is close to the weighting of the market (BLM (no view)), the indirect approach referring to the ESG mean exhibits most deviation from market weights and the median reference figures in between the two. Furthermore, Figure 5.2 depicts the difference in rebalancing to plain MV portfolio optimization, which is characterized by unstable weightings, corner solutions and thus substantial diversification deficiencies.

Another interesting aspect when considering portfolio properties over the whole period of time is the portfolio ESG score. As illustrated in Figure 5.3, the portfolios generated with the AVM outperform their benchmark in terms of ESG scores. For the period in scope, the mean referring indirect method beat the other methods, albeit the excess ESG score as compared to the median approach was rather narrow for the year 2014. Generally, the scheme found from the inspection of the weightings concerning the degree of departure from the benchmark is mirrored on the portfolio ESG score level. Moreover, Figure 5.3 also illustrates the yearly jumps in ESG scores, which due to the SMI being an index with few heavy weighted assets, is mainly depending on the ESG scores of the respective titles. However, these jumps are not a function of the different approaches, but contingent

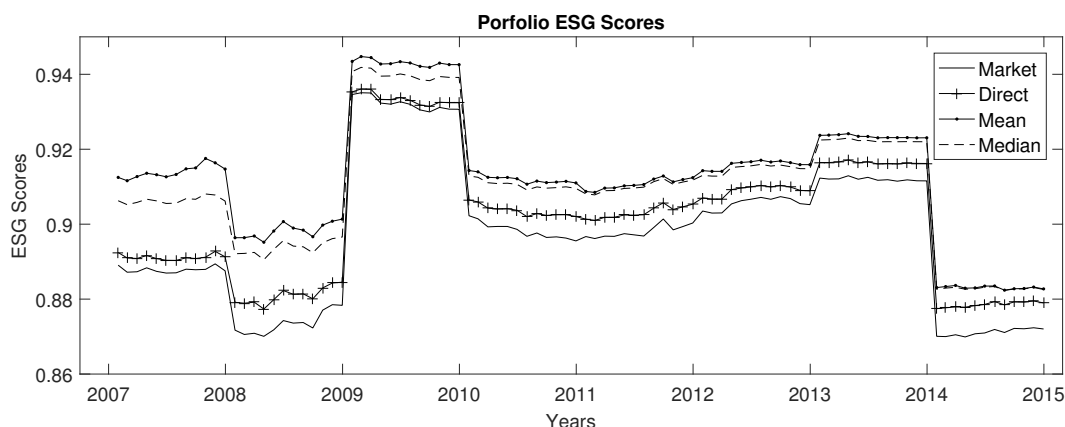


Figure 5.3 – This figure shows the monthly time series of portfolio ESG scores generated by the different portfolio weighting schemes. (Source: own figure)

on the ESG data in use. Scores updated in a higher frequency would mitigate this phenomenon. Furthermore, SMI members featuring considerable index weights happen to be attributed rather high ESG scores (see e.g. Table 5.1). Apart from this fact potentially having its cause in the correlation of firm size and ESG scores (see Section 2.4), it limits also the ESG score differentials of the generated portfolios in magnitude. Further insight into the characteristics of the different portfolios is given in Table 5.3, where different key performance measures are enlisted.

	M	$\kappa = 1$			$\kappa = 3$			$\kappa = 5$		
		D	I1	I2	D	I1	I2	D	I1	I2
ESG	0.8973	0.9020	0.9126	0.9100	0.9085	0.9232	0.9193	0.9131	0.9320	0.9250
Ret	0.0111	0.0131	0.0063	0.0094	0.0158	0.0004	0.0077	0.0176	-0.0062	0.0059
SD	0.1291	0.1285	0.1283	0.1282	0.1281	0.1277	0.1270	0.1280	0.1408	0.1264
SR	0.0858	0.1016	0.0493	0.0730	0.1231	0.0033	0.0602	0.1377	-0.0441	0.0467
TE	0.0000	0.0042	0.0076	0.0049	0.0102	0.0219	0.0117	0.0148	0.0553	0.0188
IR	0.0000	0.4659	-0.6181	-0.3482	0.4548	-0.4821	-0.2890	0.4394	-0.3096	-0.2731
α	0.0000	0.0020	-0.0046	-0.0016	0.0048	-0.0103	-0.0032	0.0066	-0.0172	-0.0048

Table 5.3 – This table contains some key performance measures for the period of 2007 to 2014. M stands for market, D for the direct and I for the indirect AVM approaches, where $I1$ refers to the mean and $I, 2$ to the median. The portfolios are calculated with different degrees of intensity of ESG incorporation, κ . The performance measures beginning from the first row are: average portfolio ESG score, average excess return over the riskfree rate, standard deviation of the returns, Sharpe Ratio, Tracking Error, Information Ratio, Jensen’s alpha. Computational details for the different measures are given in Appendix A.13.

Table 5.3 confirms the positive effect of applying the AVM approaches on the average ESG score. Furthermore, ESG scores increase as the intensity of incorporation represented by κ increases. Yet, the portfolios lose their diversification property as κ increases, and the indirect approaches are more

exposed to this effect than the direct one; e.g. with $\kappa = 5$ there are 18, 4 and 13 assets held in D , $I1$ and $I2$ portfolios. In terms of standard deviations of excess returns, the AVM approaches were able to lower this risk for low κ values, yet only the direct method D is able to outperform the market portfolio in terms of risk adjusted returns as represented by the Sharpe Ratio. A similar picture is given when comparing the Information Ratio (IR), which is the average excess return of the portfolio in consideration per unit of volatility in excess return (see e.g. Goodwin (1998)) as compared to the benchmark portfolio. The only approach that gained excess return per unit of Tracking Error (TE), i.e. per unit of risk of deviating from the market, is the direct method D . The other methods underperform in terms of risk adjusted returns relative to the market. This is mirrored in Jensen's alpha measure, that is also listed in Table 5.3, which is return generated above the prediction of the model considering the sensitivity of portfolio return movements to market return movements, β , as sole factor. Approach D generates a positive annualized alpha of 0.2% ($\kappa = 1$), 0.66% ($\kappa = 5$) respectively, while the indirect methods underperform. Yet, it is important to keep in mind that measures like the IR or Jensen's alpha in practice are supposed to measure a portfolio manager's ability to outperform the market. However, the portfolios as reported in this section are not considered to be actively managed, but they are tilt towards the incorporation of ESG measures. Accordingly, it is not a stated goal of the methods to outperform the market financially. The passive investment style is also mirrored in the relatively low tracking error measures. Furthermore, empirically, the return values and all related measures are rather low, which is also due to the chosen period containing the global financial crisis 2007-2008. For comparison reasons, key performance measures for a subsample period post financial crisis (2009-2014) is given in Table D.4 in Appendix D. Moreover, the progression of the portfolios (without consideration of transaction or similar costs) referring to an indexed starting point of 100 at the beginning of 2007 is depicted in Figure 5.4.

Thus, to draw a bottom line, according to the results of the empirical analysis it can be concluded that the AVM fulfills the goals outlined in Section 4.2 and is potentially suitable to overcome impediments to account for ESG criteria in an institutional investors context. All suggested approaches achieve the goal of increased portfolio ESG scores while maintaining market orientation. Most moderate weight shifting is achieved by applying the direct approach, which in consequence maintains diversification at even higher levels of integration intensity κ . Also, the direct approach outperforms

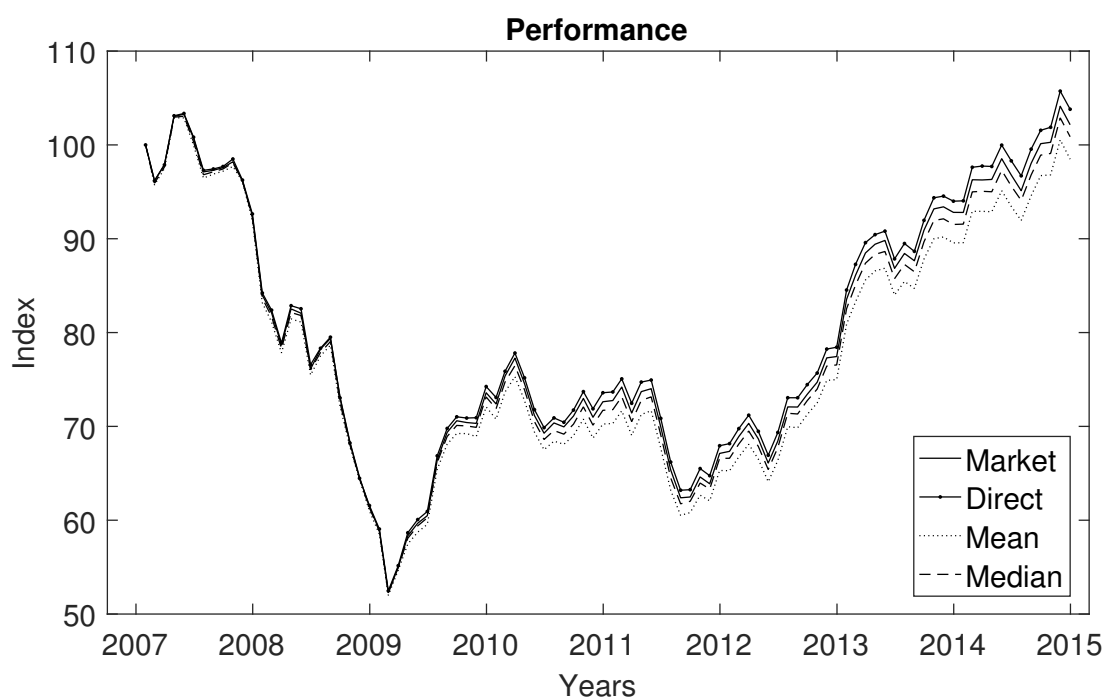


Figure 5.4 – This figure shows the monthly development of the indexed portfolio values generated by the different portfolio weighting schemes as indicated in the legend. (Source: own figure)

the market as well as the indirect approaches financially in the considered period. Yet, to conclude a systematic outperformance would be founded only on insufficient evidence and a more extensive empirical analysis with different benchmarks and periods would be necessary. The indirect methods achieve more pronounced weight shifting according to the assets' ESG scores since the according variance adjustment values cover a wider range of values. Although this statement does not hold in general, it is very likely to hold in most real data situations.

Conclusion

There are good reasons to account for environmental, social, and governmental (ESG) criteria when it comes to portfolio construction and management beyond the practice of sheer negative screening. That is, particularly considering quantitative ESG measures actively in portfolio building and rebalancing. The present thesis investigates approaches suggesting practicable frameworks for this purpose. As a matter of the nature of the problem, most of the proposed methods in the literature are contributions in the realm of Multiple Objective Optimization, which is an obvious way to tackle the problem of investment decisions based on financial risk, financial return and additional non-financial criteria as the ESG dimension. The majority of the analyzed methods share the principle of generating a non-dominated set of solutions, which basically represents a set of potential portfolios being Pareto efficient with respect to the different objectives. To determine the optimal portfolio(s), most approaches require to define an investor's preferences regarding the involved criteria. The investigated methods tackle the task of ESG incorporation either by splitting the process or the asset universe, by focusing on utility functions, using additional constraints, by applying computational concepts as Fuzzy Logic or by treating sustainable return similar to financial return. Most of the examined methods refer to Markowitz. With a tradeoff system featuring more than two components, such problems potentially reach a level of complexity that might discourage practitioners to engage in the methods in scope. Also, there still seem to be different barriers particularly for institutional investors, when it comes to implement approaches that quantitatively and permanently evaluate

ESG within the portfolio management process. One of the major impediments is the perceived detachment of the Modern Portfolio Theory paradigm and, linked to that, concerns about whether fiduciary duty of institutional investors is still fulfilled when including ESG criteria quantitatively. The method developed in this thesis is based on the Black Litterman Model and thus closely related to the mean-variance investment philosophy. To account for quantitative inclusion of ESG criteria a structure is imposed on the covariance matrix, which serves as input to a common mean-variance optimizer. As a result, the portfolio weights are shifted accordingly. Two main approaches are suggested to consider ESG scores within the proposed framework. On the one hand, the direct method: based on the assumption that there is additional information concerning the risk of a company, variance estimates are increased according to the deviation from a perfect ESG score. Thus, unless there is an asset scoring the maximum ESG score, each variance entry of the covariance matrix is penalized, yet to a different degree. On the other hand, the indirect method: the variance modification of a single title is based on the deviation of the ESG score from the mean or the median of the portfolio members' ESG scores. This causes the variance entries to be either rewarded or penalized due to the ESG performance of the respective title and - in general - weight shifting effects to be of greater magnitude as compared to the direct approach. Due to the method being related to the Black Litterman Model, the option to incorporate an investor's views to reallocate portfolio weights according to the expected financial performance remains functional. The empirical analysis confirms the portfolios generated by the implementation of the suggested method to exhibit higher ESG scores as compared to the benchmark. Highest portfolio ESG scores were attained by the mean referring variance corrective approach, as it weighs ESG performance in the most pronounced way of the approaches considered, followed by the median referring and the direct approach. Yet, this cannot be formulated as a rule, since the outcome is contingent on the data. However, variance adjustments stemming from mean and median reference are likely to be dispersed within a wider range as compared to the direct approach for most real life implementations. Concerning financial performance, only the direct method is able to outperform the market, while the two indirect approaches generate negative relative performance measures for the period in consideration. The suggested method aims at overcoming barriers for ESG incorporation by allowing for benchmark orientation, being closely related to the two dimensional mean-variance criterion space, allowing for gradational incorporation

of ESG measures, maintaining portfolio diversification while accounting for ESG criteria, providing stability in weights over time and retaining the possibility to shape the portfolio according to the investor's views on financial performance.

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Appendices

Explanatory Notes

A.1 Fama French Model

According to the three factor model of Fama and French (1996), the expected excess return of a portfolio i can be to a large extent explained by the risk premia typically compensating for the exposures to market risk, firm size and the book-to-market ratio. This relation can be expressed by the following equation

$$E(R_i) - R_f = b_i[E(R_m - R_f) + s_iE[SMB] + h_iE[HML]] \quad (\text{A.1})$$

with R_f as the risk-free rate, b_i as factor loading for the market risk for portfolio i , R_m as market return, s_i as factor loading for the difference in expected returns of small and big companies, h_i as factor loading for the difference in expected returns for growth stocks (high book-to-market ratio) vs. value stocks (low book-to-market ratio). Thus, if the findings from e.g. Van Beurden and Gössling (2008), Artiach et al. (2010)) for a ESG-market-size correlation and by Galema et al. (2008) for a ESG-book-to-market correlation are assumed to hold true, portfolios with high levels of ESG scores are likely to be less exposed to firm-size and growth risks, and thus are associated with a lower expected return, than low ESG score portfolios.

A.2 Portfolio Variance

The variance of a portfolio x is defined as follows (see e.g. Evstigneev et al. (2015)):

$$\begin{aligned}
 \sigma_x^2 &= \text{Var}(R_x) = E[(R_x - \mu_x)^2] \\
 &= E \left[\left(\sum_{i=1}^n w_i R_i - E[R_x] \right)^2 \right] = E \left[\left(\sum_{i=1}^n w_i (R_i - E[R_i]) \right)^2 \right] \\
 &= E \left[\left(\sum_{i=1}^n w_i (R_i - E[R_i]) \right) \left(\sum_{j=1}^n w_j (R_j - E[R_j]) \right) \right] \\
 &= E \left[\sum_{i=1}^n \sum_{j=1}^n w_i w_j (R_i - E[R_i]) (R_j - E[R_j]) \right] \\
 &= \sum_{i=1}^n \sum_{j=1}^n w_i w_j \text{Cov}(R_i, R_j) \\
 &= \sum_{i=1}^n \sum_{j=1}^n w_i w_j \sigma_{i,j}
 \end{aligned} \tag{A.2}$$

where generally, the covariance of two random variables X and Y is defined as

$$\text{Cov}(X, Y) = E[X - E[X]][Y - E[Y]] = E[XY] - E[X]E[Y].$$

In matrix notation the result of Expression A.2 can be written as $\mathbf{w}'\Sigma\mathbf{w}$ with \mathbf{w} being a weight vector (w_1, \dots, w_n) and Σ a matrix of the form:

$$\Sigma = \begin{bmatrix} \sigma_{1,1} & \dots & \sigma_{1,n} \\ \vdots & \sigma_{i,j} & \vdots \\ \sigma_{n,1} & \dots & \sigma_{n,n} \end{bmatrix}.$$

Generally, Σ is assumed to be strictly positive definite, i.e. $\mathbf{w}'\Sigma\mathbf{w} > 0$ for all $\mathbf{w} \neq 0$.

A.3 Diversification and the Number of Assets

The effect of diversification, or diversifying away systematic risk, can be explained mathematically as follows. Starting from the expression for portfolio variance derived in Appendix A.2, considering an equally weighted portfolio of n assets, such that $w_i = w_j = \frac{1}{n}$ for all i, j and separating the variance from the covariance terms, portfolio variance can be expressed as

$$\sigma_{PF}^2 = \frac{1}{n} \sum_{i=1}^n \frac{1}{n} \sigma_i^2 + \sum_{i=1}^n \sum_{\substack{j=1 \\ j \neq i}}^n \frac{1}{n^2} \sigma_{i,j} \quad (\text{A.3})$$

with n variance terms and $n(n-1)$ covariance terms. The average variance term is

$$\tilde{\sigma}^2 = \frac{1}{n} \sum_{i=1}^n \sigma_i^2 \quad (\text{A.4})$$

and the average covariance term is

$$\tilde{\sigma}_{i,j} = \frac{1}{n(n-1)} \sum_{i=1}^n \sum_{\substack{j=1 \\ j \neq i}}^n \sigma_{i,j}. \quad (\text{A.5})$$

The portfolio variance in equation A.3 can therefore be expressed as

$$\sigma_{PF}^2 = \frac{1}{n} \tilde{\sigma}^2 + \frac{n-1}{n} \tilde{\sigma}_{i,j}. \quad (\text{A.6})$$

The diversification effect can be observed when n tends to infinity, which causes the variance part to converge towards zero and the covariance term to the average covariance (Bodie et al., 2009).

A.4 Efficient Frontier and Pareto Optimality

The feasible set S in Figure A.1 is the set all of feasible portfolios of assets in the market in an Modern Portfolio Theory world. Minimizing portfolio variance for given levels of portfolio returns lead to solutions on the margin of the feasible set S . Yet, only the set above the global minimum variance portfolio (point m) is considered as the set of Pareto optimal solutions, which is equivalent to the efficient frontier in this context. Portfolio p in Figure A.1 is not considered as efficient since there is a portfolio with the same amount of risk but a higher return, for instance portfolio r . Thus, if this situation is translated into a MOOP framework, for portfolio p there exists a solution that is superior for at least one objective function, namely the maximization of portfolio return, i.e. p cannot belong to the set of Pareto optima. Similarly portfolio q neither is optimal according to the maximization of the expected return, nor the minimization of portfolio variance.

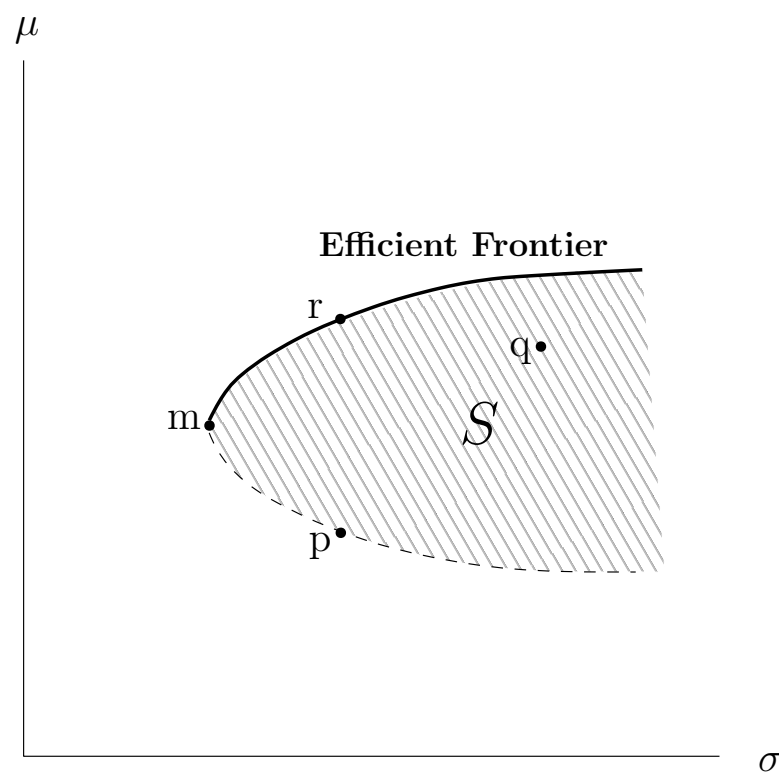


Figure A.1 – This illustration shows (a truncated set of) the efficient frontier (solid line), which is one of the main features of the Modern Portfolio Theory. The unit of the ordinate is expected return (μ) the one of the abscissa is standard deviation (σ). Point m is the global minimum variance portfolio, points p, q and r are illustrative for the explanation of Pareto optimality in the text, S is the feasible set, or in this context also called opportunity set. (Source: own figure based on Hens and Rieger (2010))

A.5 Von Neumann and Morgenstern Axioms

Von Neumann and Morgenstern (1947) define the properties of an expected utility function to model the preferences of a rational investor when faced with lottery like decisions, i.e. decisions under uncertainty. A VNM investor maximizes expected utility consistent to the following four axioms (see e.g. Hens and Rieger (2010)):

1. *Completeness*: With A and B being two alternative lotteries, either $A \succ B$, $A \sim B$, or $A \prec B$ holds. Where " \succ " stands for "is preferred to" and " \sim " symbolizes indifference.
2. *Transitivity*: With three lotteries A, B and C it must hold true that if $A \preceq B$ and $B \preceq C$ then $A \preceq C$. Where " \preceq " means "less or equally preferred to".
3. *Independence*: With $A \succ B$ and $\lambda \in (0 : 1]$, $\lambda A + (1 - \lambda)C \succ \lambda B + (1 - \lambda)C$.
4. *Continuity*: For three lotteries A, B and C of the preference order $A \succ B \succ C$, $\exists p$ (probability), s.t. $B \sim pA + (1 - p)C$.

A.6 Ideal and Nadir Vectors

The *ideal vector* in a minimization problem is the vector of m objective function values with the m th component being defined (Deb, 2014) as

$$\begin{cases} \arg \min_x & f_m(\mathbf{x}) \\ \text{subject to} & \mathbf{x} \in S, \end{cases} \quad (\text{A.7})$$

and the vector of solutions to Equation A.7 may be defined as $\mathbf{z}^* = (z_1^*, z_2^*, \dots, z_M^*)$. Typically, the ideal vector is a non-feasible solution, since the components of \mathbf{z}^* are not identical for most MOOP. A further useful vector is the *nadir vector* \mathbf{z}^{nad} , where its components are the maximum objective function values z_m^{nad} , given z_m^{nad} is element of the set of Pareto efficient solutions. Often, ideal vectors are rather easy to find, yet for nadir vectors approximation procedures are necessary. See Figure A.2 for a visual representation of the nadir and the ideal vector.

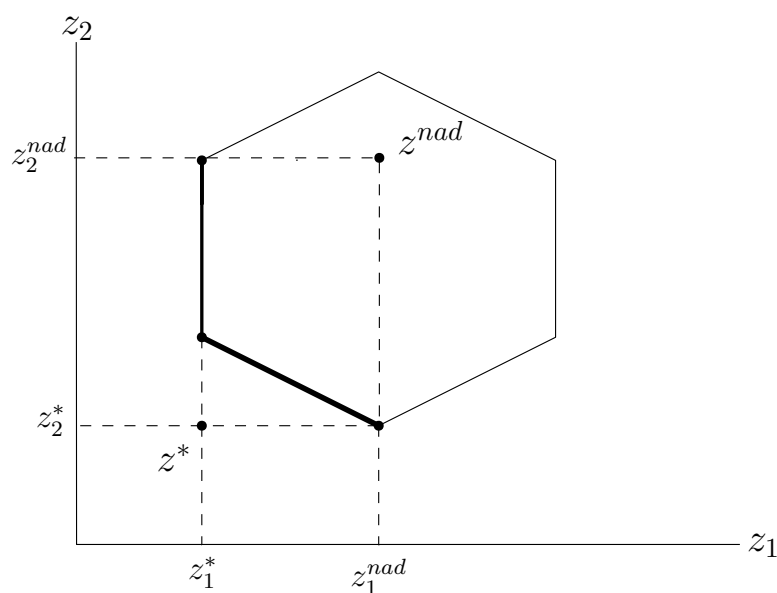


Figure A.2 – This figure depicts the ideal vector z^* as well as the nadir vector z^{nad} based on two assumed objective functions and assumed the weak form of Pareto efficiency. (Source: own figure based on Lundström and Svensson (2014); Miettinen (2012))

A.7 Risk Aversion and Concavity

The utility function in Figure A.3 is strictly concave, thus represents the preferences of a strictly risk averse agent. The latter is confronted with the lottery $E(x) = px_0 + (1 - p)x_1$ with p being a probability greater than zero. The expected utility is $E(u(x)) = pu(x_0) + (1 - p)u(x_1)$ and as a linear combination, it lies on the straight line connecting $u(x_0)$ and $u(x_1)$. A risk-neutral person would feature a utility function being equivalent to this straight line and thus would be indifferent if gambling for $E(x)$ or receiving it for sure. A risk averse person, however, values getting $E(x)$ with certainty higher than gambling for it, which is why $E(u(x)) < u(E(x))$. The difference between $E(x)$ and the certainty equivalent CE is called risk premium (RP) (see e.g. Hens and Rieger (2010)).

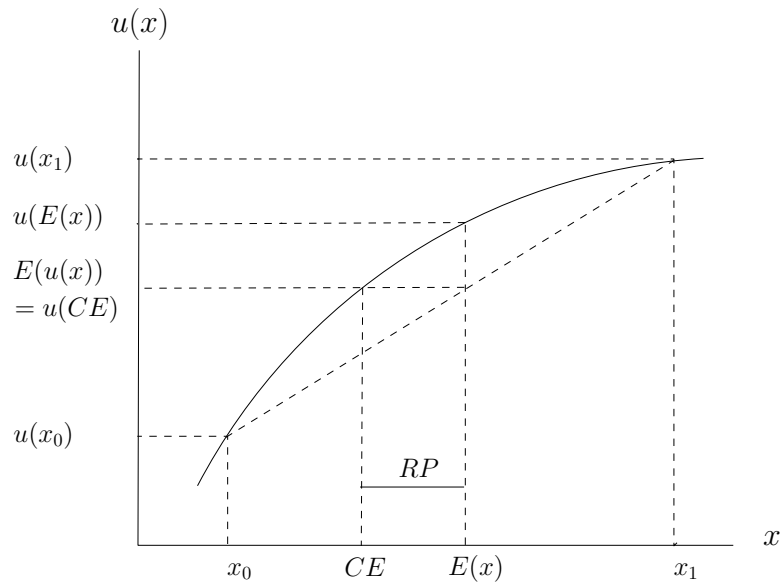


Figure A.3 – This illustration shows a strictly concave utility function in the space spanned by utility and some monetary amount x . (Source: own figure, based on Hens and Rieger (2010))

A.8 Convexity

A basic concept in the context of MOOP is the notion of convexity (Lundström and Svensson, 2014).

Definition A.1. A set S in \mathbb{R}^k is convex for all elements $x, y \in S$ and $\alpha \in [0, 1]$ if

$$\alpha x + (1 - \alpha)y \in S. \tag{A.8}$$

A function is convex on S if

$$f(\alpha x + (1 - \alpha)y) \leq \alpha f(x) + (1 - \alpha)f(y) \in S. \tag{A.9}$$

△

If the inequality in A.9 is strict, the convexity is strict. If f is convex, $-f$ is concave. If in the objective function $f(x)$ is a convex function and the feasible set S is a convex set, then the optimization problem

$$\begin{cases} \arg \min_x & f(x) \\ \text{subject to} & x \in S \end{cases} \tag{A.10}$$

is said to be a convex optimization problem.

A.9 Optimality

The general definition of optimality, not to confuse with Pareto optimality, is as follows (Lundström and Svensson, 2014):

Definition A.2. Point $x^* \in S$ is said to be a local minimizer if there exists an ϵ , s.t.

$$f(x^*) \leq f(x) \quad \forall x \in S, \text{ s.t. } \|x - x^*\| < \epsilon \in \mathbb{R}_+. \quad (\text{A.11})$$

It is a strict local minimizer if the inequality is strict.

A point $x^* \in S$ is said to be a global minimizer if

$$f(x^*) \leq f(x) \quad \forall x \in S. \quad (\text{A.12})$$

△

A.10 Problem Formulation Tri-Criterion Approach

(Hirschberger et al., 2013) start with the formulation of following problem:

$$\left\{ \begin{array}{l} \arg \min_w \quad \sqrt{z_1(\mathbf{w})} = \sqrt{\mathbf{w}'\Sigma\mathbf{w}} \\ \arg \max_w \quad z_2(\mathbf{w}) = \mu'\mathbf{w} \\ \arg \max_w \quad z_3(\mathbf{w}) = \mathbf{c}'\mathbf{w} \\ \text{subject to} \quad \mathbf{A}_l\mathbf{w} = \mathbf{a}_l \\ \quad \quad \quad \mathbf{A}_m\mathbf{w} \leq \mathbf{a}_m \\ \quad \quad \quad \mathbf{w} \geq \mathbf{l} \\ \quad \quad \quad \mathbf{w} \leq \boldsymbol{\omega} \end{array} \right. \quad (\text{A.13})$$

where

z_i	i th objective function;
\mathbf{w}	vector of N portfolio weights in the case of N risky assets;
\mathbf{w}'	vector \mathbf{w} transposed;
Σ	matrix of $N \times N$ covariances;
$\boldsymbol{\mu}$	vector of N expected returns, with $E(R_i) = \mu_i$
\mathbf{c}	vector of N quantities linked to a third goal
$\mathbf{A}_l \mathbf{w} = \mathbf{a}_l$	a set of k equality constraints containing $\mathbf{1}' \mathbf{w} = 1$;
$\mathbf{A}_m \mathbf{w} \leq \mathbf{a}_m$	a set of q inequality constraints;
\mathbf{l}	a vector of N lower bounds.
$\boldsymbol{\omega}$	a vector of N upper bounds.

The constraints in problem A.13 define the feasible set. If there are k equality constraints, then \mathbf{A} is a matrix of dimension $K \times N$ and \mathbf{a} accordingly a vector of k entries. The problem is reformulated to the multiparametric optimization problem, the optima of which are found by applying Karush-Kuhn-Tucker conditions. These are necessary first order conditions used in nonlinear programming for solutions to the problem to be optimal. The paper provides an algorithm to solve the modified problem A.13 in such a way, that the nondominated surface can be computed.⁴⁴

A.11 Market Equilibrium Considerations in CAPM

The market clearing condition requires that the asset weights in the tangential portfolio (demand side) are identical to the weights in the market portfolio. The market portfolio is equal to the wealth weighted average of I investors' portfolio weights $\mathbf{w}_i = \frac{1}{\rho_i} \Sigma^{-1} (\boldsymbol{\mu} - R_f \mathbf{1})$ (see Equation 3.6 in Section 3.2.2). Formally, this can be expressed as follows (see e.g. Sharpe (1991)):

$$\begin{aligned}
 \sum_{i=1}^I \frac{\kappa_i}{K} \mathbf{w}_i &\Rightarrow \sum_{i=1}^I \frac{\kappa_i}{K} \frac{1}{\rho_i} \Sigma^{-1} (\boldsymbol{\mu} - R_f \mathbf{1}) \\
 &= \sum_{i=1}^I \tau^i \Sigma^{-1} (\boldsymbol{\mu} - R_f \mathbf{1}) \\
 &= \tau \Sigma^{-1} (\boldsymbol{\mu} - R_f \mathbf{1})
 \end{aligned} \tag{A.14}$$

with κ_i being investor i 's wealth and K the aggregated wealth of all investors in the economy, τ_i the investor's risk tolerance and τ the aggregate average risk tolerance. The following rearrangement

⁴⁴ For details see Hirschberger et al. (2013).

steps deduce the β relation from the equilibrium condition of a clearing market:

$$\begin{aligned}
\tau \Sigma^{-1}(\boldsymbol{\mu} - R_f \mathbf{1}) &= \mathbf{w}_M \\
\Leftrightarrow (\boldsymbol{\mu} - R_f \mathbf{1}) &= \frac{1}{\tau} \Sigma \mathbf{w}_M \\
\Rightarrow \mathbf{w}'_M (\boldsymbol{\mu} - R_f \mathbf{1}) &= \frac{1}{\tau} \mathbf{w}'_M \Sigma \mathbf{w}_M \\
\Leftrightarrow (\mu_M - R_f) &= \frac{1}{\tau} \sigma_M^2 \\
\Leftrightarrow \frac{1}{\tau} &= \frac{(\mu_M - R_f)}{\sigma_M^2}
\end{aligned} \tag{A.15}$$

where \mathbf{w}_M is the weight vector of the market portfolio and σ_M^2 is the variance of the market portfolio and $\frac{1}{\tau}$ is the aggregate risk aversion coefficient (as the reciprocal value to risk tolerance) of the market. Replacing the expression for $\frac{1}{\tau}$ in the second line of derivation A.15, leads to the closed form solution of equilibrium expected returns:

$$(\boldsymbol{\mu} - R_f \mathbf{1}) = \frac{(\mu_M - R_f)}{\sigma_M^2} \Sigma \mathbf{w}_M \tag{A.16}$$

where $\Sigma \mathbf{w}_M$ is a vector of n covariances of the single assets with the market portfolio in the n asset case. Therefore, Equation A.16 can by the definition of β be reformulated to

$$(\boldsymbol{\mu} - R_f \mathbf{1}) = \beta (\mu_M - R_f) \tag{A.17}$$

with β being a vector with its k^{th} element $\beta_k = \frac{cov(R_k, R_M)}{\sigma_M^2}$. That is, the risk premium of a single asset is proportional to its contribution to the total variance of the aggregate portfolio.

A.12 Covariance Shrinking

Instead of applying simple sample covariance matrices, in this thesis the covariance shrinking method proposed in Ledoit and Wolf (2003) is applied. Generally, covariance shrinkage is the transformation of the sample covariance matrix that pulls the most extreme values towards more central values. Ledoit and Wolf (2003) achieve shrinkage by means of a linear combination of the sample covariance matrix S and a structured estimator denoted by F , that is by $\delta F + (1 - \delta)S$. The specific form of the shrinkage target F proposed in the paper is based on the average sample correlation, i.e. it is assumed that the pairwise correlations are identical. The shrinkage intensity δ is computed on the basis of the minimization of an expected quadratic loss function, minimizing the expected

distance between the true and the estimated covariance matrices, based on the Frobenius norm. For a symmetric $N \times N$ matrix with entries (z_{ij}) , $i, j = 1, \dots, N$ the Frobenius norm is defined as

$$\|Z\|^2 = \sum_{i=1}^N \sum_{j=1}^N z_{ij}^2 \quad (\text{A.18})$$

and the quadratic loss function to be minimized is accordingly

$$L(\delta) = \|\delta F + (1 - \delta)S - \Sigma\|^2. \quad (\text{A.19})$$

For further details and the source for the Matlab code applied for the present thesis in order to shrink covariance matrices, see Ledoit and Wolf (2003).

A.13 Performance Measure Calculations

Subsequently the calculations of the measures as presented in Table 5.3 from Section 5.2 are discussed.

The ESG performance for a single portfolio of N titles and portfolio weights $w_{i,t}$ for the period t is

$$ESG_{PF,t} = \sum_{i=1}^N w_{i,t-1} ESG_{i,t} \quad (\text{A.20})$$

and its arithmetic mean over the period $t = 1, \dots, T$ accordingly

$$\overline{ESG}_{PF} = \frac{1}{T} \sum_{t=1}^T ESG_{PF,t}. \quad (\text{A.21})$$

The ex post portfolio excess returns over the riskfree rate, $r_{PF,t}$ of N assets for period t are calculated as follows:

$$r_{PF,t} = \sum_{i=1}^N w_{i,t-1} r_{i,t}. \quad (\text{A.22})$$

The generic annualization of the monthly excess returns, r_m , and return related measures is computed as :

$$r_y = (1 + r_m)^{12} - 1. \quad (\text{A.23})$$

The respective standard deviations σ_m

$$\sigma_y = (\sigma_m) \times \sqrt{(12)}. \quad (\text{A.24})$$

The arithmetic mean of realized excess returns for the period $t = 1, \dots, T$ is calculated as

$$\bar{r}_{PF} = \frac{1}{T} \sum_{t=1}^T r_{PF,t} \quad (\text{A.25})$$

and the corresponding standard deviation as

$$\sigma_{PF} = \sqrt{\frac{\sum_{t=1}^T (r_{PF,t} - \bar{r}_{PF})^2}{T-1}}. \quad (\text{A.26})$$

The annualized Sharpe Ratio is accordingly

$$SR = \frac{\bar{r}_{PF,y}}{\sigma_{PF,y}}. \quad (\text{A.27})$$

Similarly, the arithmetic mean of the excess return for the portfolio return over the market return is calculated as

$$r_{PF}^D = \frac{1}{T} \sum_{t=1}^T r_{PF,t} - r_{M,t}. \quad (\text{A.28})$$

and the tracking error TE accordingly

$$TE_{PF} = \sqrt{\frac{\sum_{t=1}^T (r_{PF,t} - r_{M,t})^2}{T-1}}. \quad (\text{A.29})$$

Expressions A.28 and A.31 are the basis to calculate the IR:

$$IR_{PF} = \frac{r_{PF,y}^D}{TE_{PF,y}}. \quad (\text{A.30})$$

Finally, Jensen's alpha is calculated as follows:

$$\alpha_{PF} = \bar{r}_{PF} - \beta_{PF} \bar{r}_M \quad (\text{A.31})$$

where $\beta_{PF} = \frac{\sigma_{PF,M}}{\sigma_M^2}$, thus the fraction of the covariance of portfolio excess returns with the market portfolio excess returns and the market portfolio variance.

Proofs and Derivations

B.1 Efficiency of Weighted Sum Solutions

The solution to the problem

$$\begin{cases} \arg \min_x & F(\mathbf{x}) = \sum_{i=1}^n \lambda_i f_i(\mathbf{x}) \\ \text{subject to} & \mathbf{x} \in S \end{cases} \quad (\text{B.1})$$

is weakly Pareto efficient if $\lambda_i \geq 0$ for all $i \in (1, \dots, n)$. This is proven by contradiction: Let \mathbf{x}^* be a solution to Problem B.1. To show that \mathbf{x}^* is a weakly efficient solution to the MOOP A.10 suppose that there exists some $\tilde{\mathbf{x}} \in S$, such that $f_i(\tilde{\mathbf{x}}) < f_i(\mathbf{x}^*)$, for all $i \in (1, \dots, n)$, i.e. suppose that \mathbf{x}^* is not weakly efficient. This implies that $\sum_{i=1}^n \lambda_i f_i(\tilde{\mathbf{x}}) < \sum_{i=1}^n \lambda_i f_i(\mathbf{x}^*)$ due to the non-negativity of the weights. This is a contradiction to \mathbf{x}^* being a solution to B.1, thus \mathbf{x}^* is weakly efficient.

For the proof of strict efficiency, the weights are required to be $\lambda_i > 0$ for all $i \in (1, \dots, n)$. Similar to the proof above, it is assumed that there exists some $\tilde{\mathbf{x}} \in S$, such that $f_i(\tilde{\mathbf{x}}) \leq f_i(\mathbf{x}^*)$, for all $i \in (1, \dots, n)$, with at least one strict inequality. This again implies that

$\sum_{i=1}^n \lambda_i f_i(\tilde{\mathbf{x}}) < \sum_{i=1}^n \lambda_i f_i(\mathbf{x}^*)$ due to the weights being strictly positive. This is a contradiction and \mathbf{x}^* is strictly efficient.

B.2 Efficiency of ϵ -Constraint Solutions

Let the solution \mathbf{x}^* to the problem

$$\begin{cases} \arg \min_x & f_j(\mathbf{x}) \\ \text{subject to} & f_i(\mathbf{x}) \leq \epsilon_i, i = (1, \dots, k), \forall i \neq j \\ & \mathbf{x} \in S. \end{cases} \quad (\text{B.2})$$

be an optimal solution, then this solution is weakly efficient. For a proof assume \mathbf{x}^* is not weakly efficient, then there is some $\mathbf{x} \in S$ with $f_i(\mathbf{x}) < f_i(\mathbf{x}^*)$ for all $i = (1, \dots, k)$, particularly $f_j(\mathbf{x}) < f_j(\mathbf{x}^*)$. Also, the solution is feasible since $f_i(\mathbf{x}) < f_i(\mathbf{x}^*) \leq \epsilon_i$ for $i \neq j$. This contradicts \mathbf{x}^* being an optimal solution to B.2.

To prove that \mathbf{x}^* is also a strictly efficient solution, assume that \mathbf{x}^* is optimal and unique. Assume further that there is some $\mathbf{x} \in S$ with $f_i(\mathbf{x}) \leq f_i(\mathbf{x}^*) \leq \epsilon_i$ for all $i \neq j$. If additionally, it is assumed that $f_j(\mathbf{x}) \leq f_j(\mathbf{x}^*)$, it must hold that $f_j(\mathbf{x}) = f_j(\mathbf{x}^*)$, because \mathbf{x}^* is an optimal solution to Problem B.2. The uniqueness of \mathbf{x}^* thus implies $\mathbf{x} = \mathbf{x}^*$ and the strict efficiency of \mathbf{x}^* .

For \mathbf{x}^* to be strictly efficient, in general, it is required that $\epsilon_i = f_i(\mathbf{x}^*)$ for $i = (1, \dots, k)$. If this is not the case, then there exists some feasible solution \mathbf{x} with $f_j(\mathbf{x}) < \epsilon_j$ for some j and $f_k(\mathbf{x}) \leq \epsilon_k$ for all $k \neq j$. This contradicts the optimality assumption of \mathbf{x}^* .

B.3 Derivation of the CAPM formula

There are different ways of deriving the core expression of the CAPM relating the expected return of an asset j to its co-movement with the market portfolio. One straight forward approach is given in Bodie et al. (2009). Due to equilibrium considerations it must hold that the risk-to-reward ratio of the market portfolio must be equal to one of asset j . If the converse was true, this would mean that the market portfolio is not efficient and that it would have to be changed by shifting weights towards the superior asset, such that consequently it must hold that both risk-to-reward ratios are equal. Therefore, note that the covariance of asset j with the market portfolio can be defined as follows:

$$Cov(R_M, R_j) = Cov(R_j, \sum_{k=1}^n w_k R_k) = \sum_{k=1}^n w_k Cov(R_k, R_j) \quad (\text{B.3})$$

while asset j contributes to the market portfolio risk by $w_j \text{Cov}(R_j, R_m)$, similarly the reward contribution to the market portfolio can be expressed as $w_j(\mu_j - R_f)$. Setting equal both risk-to-reward ratios (the weights w_j cancel out) yields:

$$\frac{\mu_j - R_f}{\text{Cov}(R_M, R_j)} = \frac{\mu_M - R_f}{\sigma_M^2} \quad (\text{B.4})$$

and solving for $\mu_j - R_f$ and replacing $\frac{\text{Cov}(R_M, R_j)}{\sigma_M^2}$ by β leads to the CAPM centerpiece

$$\mu_j - R_f = \beta_j(\mu_M - R_f). \quad (\text{B.5})$$

B.4 Derivation of the BLM Master Formula

The following derivation is based on the work of Satchell and Scowcroft (2000), Christodoulakis (2002) and comments as well as explanations from Zuber (2012). The following paragraphs derive that the posterior distribution is defined by

$$\begin{aligned} \mu_p &= (\tau\Sigma)^{-1} + P'\Omega^{-1}P]^{-1}[(\tau\Sigma)^{-1}\Pi + P'\Omega^{-1}Q] \\ \Sigma_P &= [(\tau\Sigma)^{-1} + P'\Omega^{-1}P]^{-1}. \end{aligned} \quad (\text{B.6})$$

The BLM posterior distribution according to Bayes' theorem is postulated as

$$\text{pdf}(\mu | \Pi) = \frac{\text{pdf}(\Pi | \mu) \times \text{pdf}(\mu)}{\text{pdf}(\Pi)}. \quad (\text{B.7})$$

In a multivariate setting as it is encountered in the case of a vector of expected returns, generally a density function of a $(N \times 1)$ vector $x = (x_1, x_2, \dots, x_N)$ is denoted as follows:

$$f(x | m, V) = (2\pi_c)^{-n/2} |V|^{-\frac{1}{2}} \exp \left[-\frac{1}{2} (x - m)' V^{-1} (x - m) \right], \quad (\text{B.8})$$

with π_c as the mathematical constant, \exp as the exponential function, m being a $(N \times 1)$ vector $m = (m_1, m_2, \dots, m_N)$ of means, V being the $(N \times N)$ covariance matrix, $|V|$ its determinant and V^{-1} its inverse. The normalizing constant $\text{pdf}(\Pi)$ from Expression B.7 will disappear into the constant of integration with respect to μ , thus the focus lies on the numerator. Having defined in Section 4.1 that $\mu \sim N(\Pi, \tau\Sigma)$ and $P\mu \sim (Q, \Omega)$, hence the density function of the conditional probability is

$$\text{pdf}(\Pi | \mu) = (2\pi_c)^{-n/2} |\tau\Sigma|^{-\frac{1}{2}} \exp \left[-\frac{1}{2} (\Pi - \mu)' (\tau\Sigma)^{-1} (\Pi - \mu) \right] \quad (\text{B.9})$$

and the density function of the prior is

$$pdf(\mu) = (2\pi_c)^{-n/2} |\Omega|^{-\frac{1}{2}} \exp \left[-\frac{1}{2} (P\mu - Q)' \Omega^{-1} (P\mu - Q) \right]. \quad (\text{B.10})$$

Since in both Expressions B.9 and B.10, the terms of the form $(2\pi_c)^{-n/2} |V|^{-\frac{1}{2}}$ are constant, there is no influence on the proportion to the posterior distribution, thus the focus on the nominator of Expression B.7 leaves us with

$$\exp \left[-\frac{1}{2} (\Pi - \mu)' (\tau\Sigma)^{-1} (\Pi - \mu) - \frac{1}{2} (P\mu - Q)' \Omega^{-1} (P\mu - Q) \right]. \quad (\text{B.11})$$

and expanding Expression B.11 further leads to

$$\exp \left[-\frac{1}{2} (\Pi' (\tau\Sigma)^{-1} \Pi - \Pi' (\tau\Sigma)^{-1} \mu - \mu' (\tau\Sigma)^{-1} \Pi + \mu' (\tau\Sigma)^{-1} \mu \right. \\ \left. + (P\mu)' \Omega^{-1} P\mu - (P\mu)' \Omega^{-1} Q - Q' \Omega^{-1} P\mu + Q' \Omega^{-1} P\mu Q \right] \quad (\text{B.12})$$

Since $(\tau\Sigma)^{-1}$ and Ω^{-1} are symmetric, B.12 can be simplified to

$$\exp \left[-\frac{1}{2} (\mu' ((\tau\Sigma)^{-1} + P' \Omega^{-1} P) \mu - 2((\tau\Sigma)^{-1} \Pi + P \Omega^{-1} Q)' \mu + \Pi' (\tau\Sigma)^{-1} \Pi + Q' \Omega^{-1} Q) \right]. \quad (\text{B.13})$$

Let us define

$$\begin{aligned} Z &\equiv ((\tau\Sigma)^{-1} + P' \Omega^{-1} P) \\ C &\equiv (\tau\Sigma)^{-1} \Pi + P \Omega^{-1} Q \\ A &\equiv \Pi' (\tau\Sigma)^{-1} \Pi + Q' \Omega^{-1} Q \end{aligned} \quad (\text{B.14})$$

where Z is symmetric and thus $Z' = Z$. Expression B.13 is reformulated to

$$\exp \left[-\frac{1}{2} (\mu' Z \mu - 2C' \mu + A) \right]. \quad (\text{B.15})$$

Multiplication of $\mu' Z \mu$ and $C' \mu$ of Expression B.13 with $Z^{-1} Z = I$, where I is the $(N \times N)$ identity matrix leads to

$$\exp \left[-\frac{1}{2} (\mu' Z' Z^{-1} Z \mu - 2C' Z^{-1} Z \mu + A) \right]. \quad (\text{B.16})$$

Based on the symmetry of Z and the fact that

$$\begin{aligned} (Z\mu - C)' Z^{-1} (Z\mu - C) &= (Z\mu)' Z^{-1} Z\mu - (Z\mu)' Z^{-1} C - C' Z^{-1} Z\mu + C' Z^{-1} C \\ &= (Z\mu)' \mu - 2C' Z^{-1} Z\mu + C' Z^{-1} C \end{aligned} \quad (\text{B.17})$$

Expression B.16 can be rearranged into

$$\exp \left[-\frac{1}{2} ((Z\mu - C)' Z^{-1} (Z\mu - C) - C' Z^{-1} C + A) \right] \quad (\text{B.18})$$

and since it holds that $(Z\mu - C) = (\mu - Z^{-1}C)Z$, B.18 is reformulated as follows

$$\exp\left[-\frac{1}{2}((\mu - Z^{-1}C)'Z(\mu - Z^{-1}C) - C'Z^{-1}C + A)\right]. \quad (\text{B.19})$$

When integrating with respect to μ , A and $C'Z^{-1}C$ disappear as constant, thus the proportionality of the posterior density function can be expressed as

$$pdf(\mu | \Pi) \propto \exp\left[-\frac{1}{2}((\mu - Z^{-1}C)'Z(\mu - Z^{-1}C))\right] \quad (\text{B.20})$$

where \propto indicates proportionality. Comparing B.8 with B.20, it is straight forward to identify the posterior mean

$$\mu_p = [Z^{-1}C] = [(\tau\Sigma)^{-1} + P'\Omega^{-1}P]^{-1}[(\tau\Sigma)^{-1}\Pi + P'\Omega^{-1}Q] \quad (\text{B.21})$$

as well as its variance

$$\Sigma_P = [(\tau\Sigma)^{-1} + P'\Omega^{-1}P]^{-1} \quad (\text{B.22})$$

being the components of the BLM master formula.

Figures

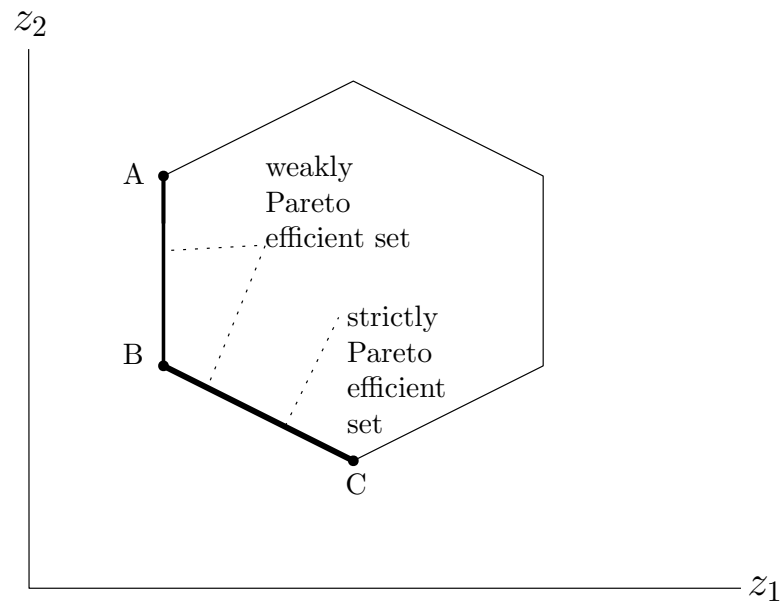


Figure C.1 – This illustration shows the weakly and the strictly Pareto efficient set in the image of two objective functions z_1 and z_2 in a minimization setup. For the set on the bold lines between points A , B and C (including A, B, C) it holds true that there does not exist any \mathbf{x} that lowers the values for all objective functions at the same time, which by Definition 3.1 makes the set weakly Pareto efficient. However, focusing on point A for illustration purposes, points south of A (except for point B) exhibit lesser z_1 values while z_2 values remain the same, thus by definition A it is not considered strictly efficient. This reasoning holds true for the set between A and B (including A , excluding B). For the set between B and C (including both), such \mathbf{z} (and accordingly \mathbf{x}) do not exist, making it the strictly Pareto efficient set. (Source: own figure based on Lundström and Svensson (2014); Miettinen (2012))

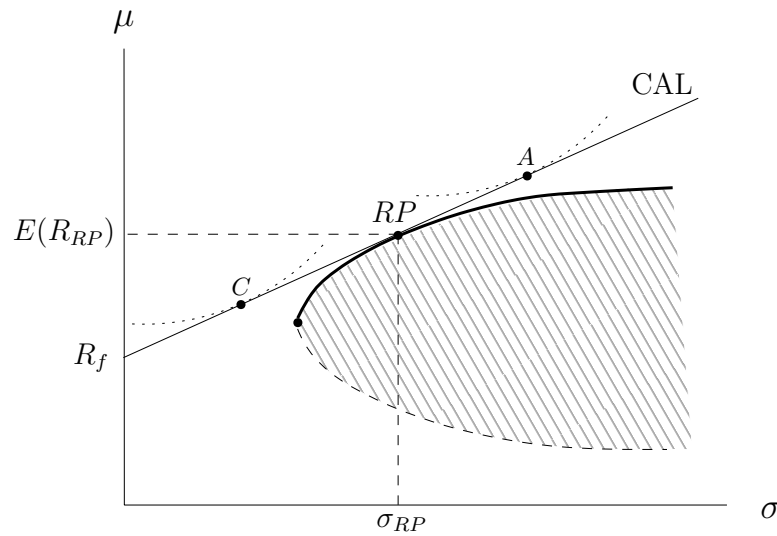


Figure C.2 – This illustration shows the CAL, which is set of all combinations of the riskfree asset R_f and the risky portfolio RP (or the tangential portfolio). Generic investor C being a conservative investor according to her risk aversion parameter lends, the more aggressive investor A borrows money at the rate of R_f to buy more of the RP . The dotted lines passing through points A and C represent respective indifference curves of the investors. The risky portfolio RP with an expected return $E(R_{RP})$ and standard deviation σ_{RP} is the tangential point of the CAL being the tangent to the Efficient Frontier (bold line). The slope of the CAL is equal to $\frac{E(R_{RP}) - R_f}{\sigma_{RP}}$, which is the maximal attainable Sharpe Ratio, defined as $\frac{E(R_i) - R_f}{\sigma_i}$ in this setup. (Source: own figure based on Bodie et al. (2009))

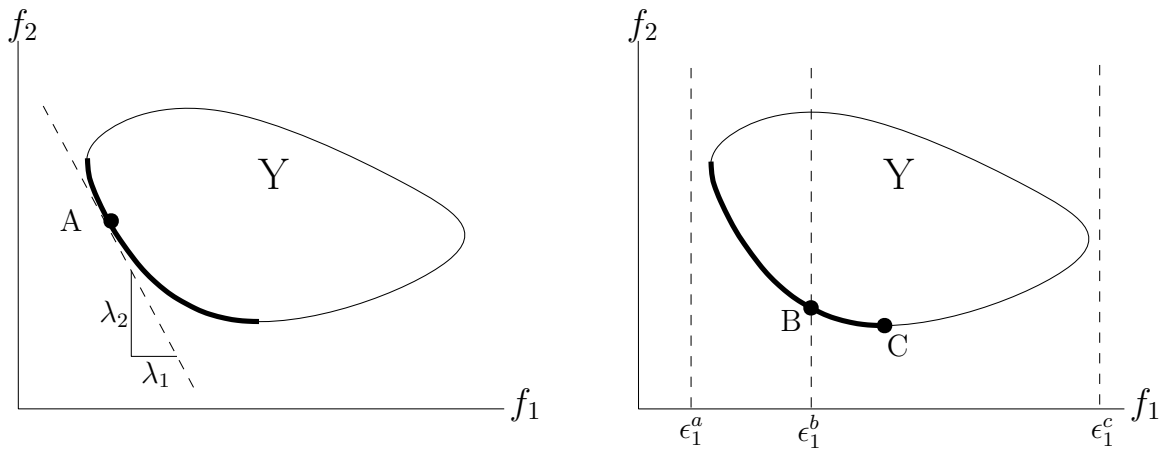


Figure C.3 – This illustration shows the weighted sum approach on the left, the ϵ -constraint on the right schematically in the case of two objective functions. The feasible set in the objective space is the area labeled with Y , the Pareto efficient set is the bold line. On the left, the choice of weights determines the slope of the curve being tangential to the feasible set in the objective space Y , with the tangential point A as one efficient solution to the MOOP. On the right hand side different levels of ϵ_1 values illustrate the mechanics of the ϵ -constraint method. In this example f_2 is the function to optimize for, while f_1 is treated as constraint, (alternatively, this could equivalently have been labeled in the Z space). If the starting value is ϵ_1^a no solution is found, since the feasible set lies on the right hand side of the constraint. For the starting value being ϵ_1^b and the feasible set being on the left side of the constraint, point B is found as an efficient solution. Choosing ϵ_1^c as starting value, point C on the efficient set is found. (Source: own figure based on Deb (2014))

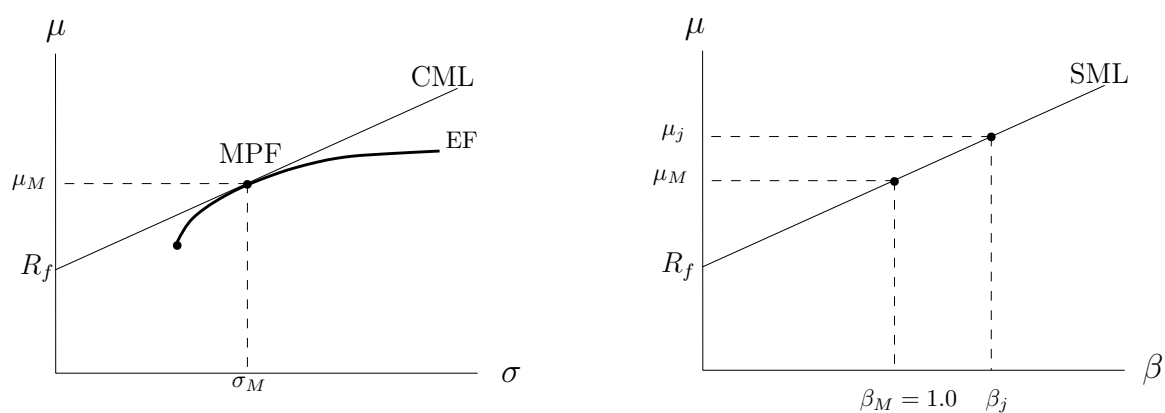


Figure C.4 – This illustration shows the Capital Market Line (CML) on the left hand side. It is a projection of the market equilibrium when all investors act based on homogeneous beliefs and planning horizons in accordance with the MPT. The Capital Allocation Line (CAL) from the single investor's optimization problem becomes the CML and the tangential portfolio becomes the Market Portfolio (MPF). On the right hand side the Security Market Line (SML) depicts the relation of the risk measure β and the expected return μ . Its slope is $\mu_M - R_f$ since β as a measure for exposure to movements of the market portfolio is equal to one for the market portfolio. Asset j for illustrative reasons bears a β greater than one which induces a higher expected return as compared to the MPF. (Source: own figure based on Bodie et al. (2009))

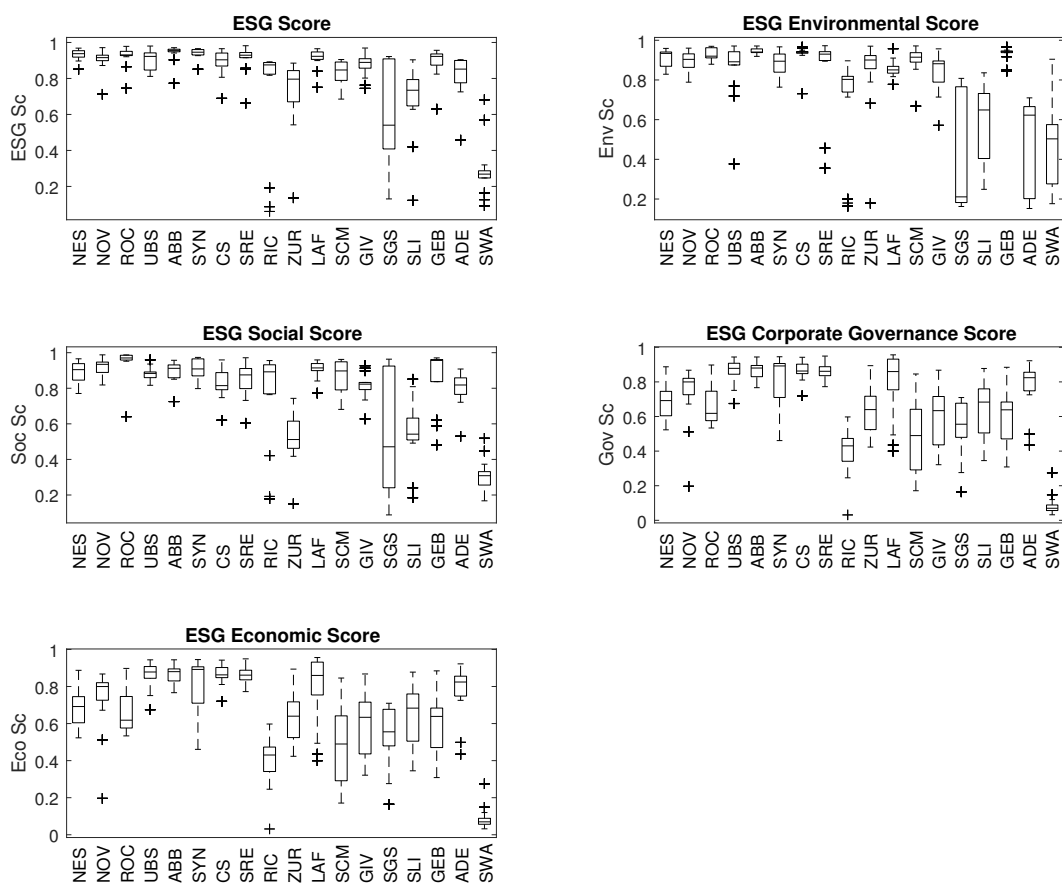


Figure C.5 – This figure shows the distribution of the ESG data by means of boxplots, beginning on the top left with the equally weighted ESG score for each of the titles, followed by the single category scores. The boxplots are based on yearly data from 2002 to 2014. (Source: own figure)

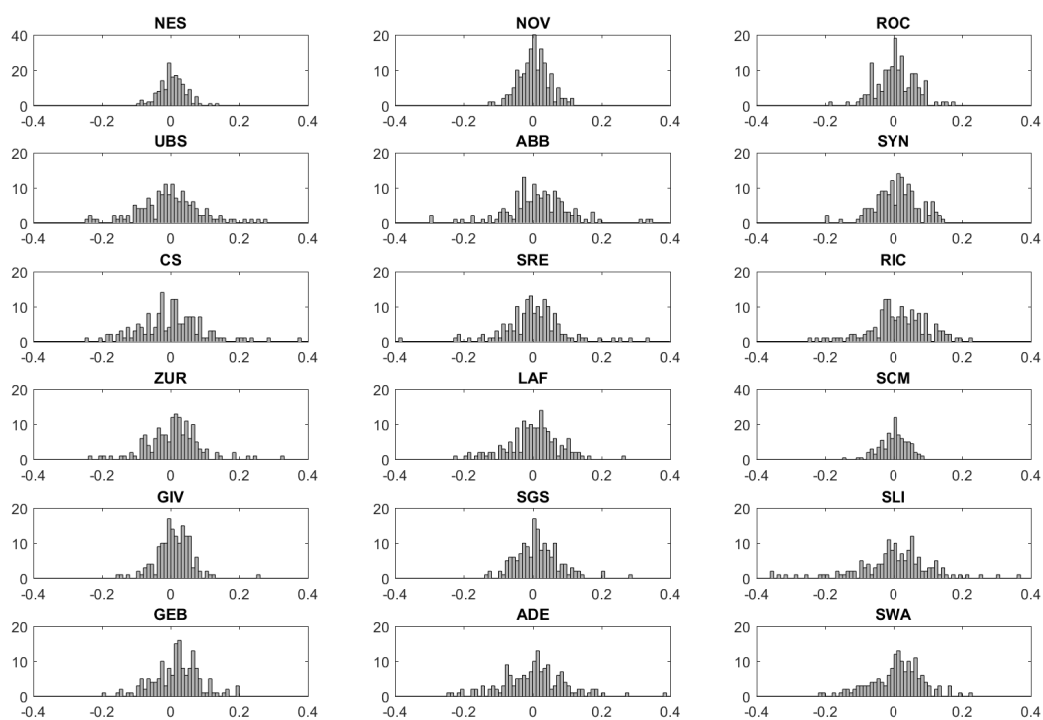


Figure C.6 – This figure shows the histograms of monthly returns from January 2002 to December 2014 for the single members of the SMI(-). (Source: own figure)

Appendix D

Tables

Eurosif	GSIA	PRI	EFAMA
Exclusions	ESG Negative screening	ESG Negative / Exclusionary screening	Negative Screening or Exclusion
Norms-based screening	Norms-based screening	Norms-based screening	Norms-based approach
Best-in Class selection	ESG Positive screening and Best-in-Class	ESG Postive screening and Best-in-Class	Best-in-Class policy
Sustainability themed	Sustainability themed	ESG themed Investments	Thematic Investment
ESG Integration	ESG Integration	Integration of ESG issues	-
Engagement and voting	Corporate Engagement and shareholder action	Engagement	Engagement
Impact Investing	Impact / Community investing	-	-

Table D.1 – ESG Strategies in different networks

Source: Eurosif (2014)

Company	Weight(%)
NESTLE	21.1812
NOVARTIS	22.5019
ROCHE	17.0730
UBS	5.7197
ABB	4.4059
SYNGENTA	2.6780
CREDIT SUISSE	3.6292
SWISS RE	2.7920
RICHEMONT	4.1736
ZURICH	4.1982
LAFARGE HOLCIM	2.1013
SWISSCOM	2.4370
GIVAUDAN	1.4906
SGS	1.4403
SWISS LIFE	0.6828
GEBERIT	1.1517
ADECCO	1.1101
SWATCH	1.2334

Table D.2 – This table shows the members of the SMI(-) that are used in the empirical analysis part. The weights are indicative as of end of December 2014, adjusted for the two excluded assets due to data completeness considerations.

ESG Category	Description
Environmental	The environmental pillar measures a company's impact on living and non-living natural systems, including the air, land and water, as well as complete ecosystems. It reflects how well a company uses best management practices to avoid environmental risks and capitalize on environmental opportunities in order to generate long term shareholder value.
Social	The social pillar measures a company's capacity to generate trust and loyalty with its workforce, customers and society, through its use of best management practices. It is a reflection of the company's reputation and the health of its license to operate, which are key factors in determining its ability to generate long term shareholder value.
Corporate Governance	The corporate governance pillar measures a company's systems and processes, which ensure that its board members and executives act in the best interests of its long term shareholders. It reflects a company's capacity, through its use of best management practices, to direct and control its rights and responsibilities through the creation of incentives, as well as checks and balances in order to generate long term shareholder value.
Economic	The economic pillar measures a company's capacity to generate sustainable growth and a high return on investment through the efficient use of all its resources. It is reflection of a company's overall financial health and its ability to generate long term shareholder value through its use of best management practices.

Table D.3 – This table shows the exact specification of the Asset4 categories as given by Thomson Reuters.

	M	$\kappa = 1$			$\kappa = 3$			$\kappa = 5$		
		D	I1	I2	D	I1	I2	D	I1	I2
ESG	0.8973	0.9020	0.9126	0.9100	0.9085	0.9232	0.9193	0.9131	0.9320	0.9250
Ret	0.0111	0.0131	0.0063	0.0094	0.0158	0.0004	0.0077	0.0176	-0.0062	0.0059
SD	0.1291	0.1285	0.1283	0.1282	0.1281	0.1277	0.1270	0.1280	0.1408	0.1264
SR	0.0858	0.1016	0.0493	0.0730	0.1231	0.0033	0.0602	0.1377	-0.0441	0.0467
TE	0.0000	0.0042	0.0076	0.0049	0.0102	0.0219	0.0117	0.0148	0.0553	0.0188
IR	0.0000	0.4659	-0.6181	-0.3482	0.4548	-0.4821	-0.2890	0.4394	-0.3096	-0.2731
α	0.0000	0.0020	-0.0046	-0.0016	0.0048	-0.0103	-0.0032	0.0066	-0.0172	-0.0048
ESG	0.8973	0.9026	0.9096	0.9086	0.9082	0.9183	0.9163	0.9121	0.9253	0.9218
Ret	0.0731	0.0745	0.0696	0.0716	0.0759	0.0646	0.0694	0.0765	0.0631	0.0675
SD	0.1003	0.0991	0.0997	0.0993	0.0980	0.0999	0.0985	0.0975	0.0994	0.0982
SR	0.7287	0.7512	0.6982	0.7206	0.7739	0.6473	0.7053	0.7848	0.6348	0.6877
TE	–	0.0036	0.0049	0.0049	0.0085	0.0129	0.0117	0.0121	0.0223	0.0188
IR	–	0.3676	-0.6604	-0.3535	0.3061	-0.6120	-0.3627	0.2699	-0.4195	-0.3557
α	–	0.0022	-0.0028	-0.0007	0.0045	-0.0070	-0.0018	0.0057	-0.0070	-0.0030

Table D.4 – The upper half of this table corresponds to Table 5.3 and contains some key performance measures for the period of 2007 to 2014. The lower half contains key measures for the subsample period excluding the global financial crises, thus 2009-2014, for comparison reasons. M stands for market, D for the direct and I for the indirect AVM approaches, where $I1$ refers to the mean and $I2$ to the median. The portfolios were calculated due to different degrees of intensity of ESG incorporation, κ . The performance measures beginning from the first row: ESG average score, average excess return over the riskfree rate, standard deviation of the returns, Sharpe Ratio, Tracking Error, Information Ratio, Jensen’s alpha. Computational details for the different measures are given in Appendix A.13.