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SOCIALLY RESPONSIBLE INVESTMENTS

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Within the last two decades, the market of socially responsible investing (SRI) has seen unprecedented growth and has become more and more important, not only because of the current financial crisis. This chapter gives a survey of the asset class SRI in general, i.e., market development and investment possibilities. Moreover, the question "How sustainable is sustainability?" is addressed by analyzing SAM Group sustainability rankings of the years 2001–2007. Furthermore, the ability of SRI to contribute to diversification within a portfolio is scrutinized. The analysis is based on simulated returns generated by an autoregressive Markov-Switching model and accounts for different levels of investors' risk aversion. Optimal portfolios consisting of stocks, bonds, and the respective SRI index show that risk–averse investors mix SRI to an established portfolio consisting of bonds and stocks to reduce the risk and increase the performance. Additionally, the asset class SRI is found to be a substitute for the asset class stocks.

1.1. INTRODUCTION

There are different ways to describe socially responsible investing (SRI). Reference 1 defines SRI as the integration of environmental, social, and corporate governance (ESG) considerations into investment management processes and ownership practices hoping that these factors can have an impact on financial performance. Responsible investment can be practiced across all asset classes.

Several reasons can be stated, why the field of SRI has gained great public interest as well as rising economic importance in recent years. Simultaneously to the on-going climate change debate, public scrutiny and political attention have put pressure on businesses to consider both social and environmental issues in their activities.

Accompanied by these developments, the SRI market grew strongly during the last decade. SRI does no longer represent a negligible economical niche, but as stated in [2] it might play a crucial financial role in the future. The current size of the worldwide SRI market is according to [3] approximately €5 trillion. With 53% market share, the greatest part of the SRI market is based in Europe followed by the United States with 39%. The rest of the world represents only 8% of the SRI market.

According to [4], the size of the SRI market in the United States was $639 billion in 1995 and then grew up to $2159 billion in 1999, which means an average annual growth rate of 36%. From 1999 to 2005, SRI investment volumes only slightly grew up to $2290 billion, but then growth accelerated again resulting in $2711 billion in 2007.

The European SRI market experienced an average growth rate of 51% since 2002 from an absolute investment volume of €336 billion in 2002 up to €2665 billion in 2007. Reference 3 estimates that the share of SRI in the total European fund market is about 17.6% in 2008 and largely driven by institutional investors.

There are several possibilities to invest into SRI. For example, the SAM Group (www.sam-group.com) offers a wide range of funds covering the total SRI market and also special funds, e.g., on Islamic sustainability. There are also sustainably managed fixed-income funds available. Another possibility is the direct investment into non-listed companies or projects. In this context, projects like wind farms or solar parks can be mentioned as suitable investment possibilities. Moreover, certificates are available on the market which allow the investor to participate in the SRI market, e.g., index certificates on the European Renewable Energy Index (ERIX Index Certificate, Societe Generale, ISIN: DE000SG1ERX7).

The structure of this chapter is as follows. Section 1.2 gives an overview on recent research on SRI. Section 1.3 answers the question "How sustainable is sustainability?" by using Markov transition matrices. Section 1.4 then analyzes SRI in a portfolio context by generating optimal portfolios for different investors using a Markov-Switching model and different optimization frameworks. Finally, Sec. 1.5 concludes.

1.2. RECENT RESEARCH ON SRI

During the last years, several empirical studies analyzed whether SRI produces or destroys shareholder wealth. Many early studies on the performance of SRI use regression models with one or two factors and try to measure Jensen's alpha. Reference 5 compares 32 SRI funds to 320 non-SRI funds in the United States between 1981 and 1990 and finds no significant average alphas with respect to a value-weighted NYSE index. More advanced studies apply a matching approach to compare SRI and non-SRI funds with similar characteristics, e.g., fund universe and size. Within this approach, management and transaction costs can be included into the analysis, see, e.g., [6] or [7]. As a result, no significant performance differences between SRI and non-SRI could be observed. One problem is that important characteristics might not be taken into consideration. Reference 8 applies a four factor model according to [9] using as regression factors the excess market return, SMB ("Small-minus-Big": The difference between the return of a small- and of a large-cap portfolio), HML ("High-minus-Low": The return difference between a value- and a growth-portfolio, i.e., a portfolio containing firms that dispose of a high book-to-market ratio versus firms with a low value relating to this ratio), and MOM ("Momentum": The return difference betweeen two portfolios, one consisting of last year's best performers and the other of the worst performers) in order to analyze the performance of United States, German, and British SRI funds. The authors build two portfolios for each country, one containing all SRI funds, the other the conventional funds, and find under — as well as outperformance of SRI, but none of the differences are significant. Furthermore, SRI funds seem to have an investment bias toward growth stocks (low book-to-market value) and small caps (lower market-capitalization). Reference 10 uses eco-efficiency rankings of Innovest to evaluate two equity portfolios that differ in eco-efficiency. The high-ranked portfolio shows significantly higher returns than its low-ranked counterpart over the period 1995–2003. In contrast, [11] finds that SRI investors have to pay for their constrained investment style. Another approach is to look at SRI equity indices to avoid usual problems of mutual funds during a performance analysis, e.g., transaction costs of funds or effects of management skills. Reference 12 analyzes 29 SRI indices and applies different settings to test for differences in risk-adjusted performance compared to a suitable benchmark. The study concludes that SRI screens do not lead to significant performance difference of SRI indices. Yet, no final answer to the question whether SRI produces or destroys shareholder wealth can be given. Independent of these findings, SRI market growth might simply come from the non-financial utility gained by SRI investors. To the authors' best knowledge, there is yet no such study scrutinizing this effect. Therefore, the focus of Sec. 1.4 lies on the benefits of SRI in a portfolio context. For this, optimal portfolios of bonds, stocks, and SRI will be constructed for different investor types and in different optimization frameworks.

1.3. HOW SUSTAINABLE IS SUSTAINABILITY?

In this section, the endurance of sustainability is analyzed. This is especially important for an SRI investor, who does not want to have too many reallocations in his portfolio. Moreover, sustainability scores should be enduring by the pure definition of the word "sustainability". For this aim, sustainability scores from SAM Group, one of the world's most respected companies in the field of SRI assessment, are scrutinized. This study is implemented using Markov transition matrices.

1.3.1. Description of the Dataset

The dataset used for the analysis contains the sustainability scores (hereinafter called total score) of 822 companies. The methodology for calculating the total score of a firm is given as follows. A company's economic, ecologic, and social performance is analyzed, where each of the three dimensions is divided into several criteria. These criteria are weighted with an individual percentage of contribution to derive the final total score. There are general criteria for all industries and specific criteria for companies in a certain sector.

The complete dataset consists of 4432 total scores for the different firms and years between 2001 and 2007. However, not every company receives a sustainability score by SAM every year, simply due to the fact that there are firms that are not willing to participate in the assessment process every year. To be more precise, only 185 companies were evaluated by SAM Group in every single of the seven assessment years. The companies in the dataset are a mixture of worldwide well-known multinational companies, such as Adidas AG, Allianz SE, the Coca-Cola Company, and Sony Corporation, as well as rather regional established firms such as Eniro AB from Sweden or the Italian Beni Stabili SpA. It can be seen from Table 1.1 that the total scores over the whole time period range between a rather low rating of 4.97 and a very high score of 92.37, i.e., that the predefined range between 0 and 100 is actually utilized. Interestingly, the median and mean of the overall total scores are slightly above 50, and barely half of the companies received a sustainability score between 43 and 65.

1.3.2. Introduction to Markov Transition Matrices

In this section, Markov transition matrices are used to analyze the evolution of the sustainability scores. A high degree of variation within the total scores would be

Table 1.1 Statistics on Total Score.

Minimum	1st quartile	Median	Mean	3rd quartile	Maximum
4.97	43.60	55.48	53.67	65.19	92.37

counter-intuitive, due to the fact that sustainability is a long-term affair and thus should not be subject to large-sized jumps, unless extraordinary events occur, e.g., an environmental disaster on an oil producer's platform. For the following analysis, data of those companies are used for which the sustainability scores are available for two consecutive years. For the entire six-year time period, this leads to a total dataset of 2125 observations. The calculation of the transition matrices is performed as follows: For every single year, companies are ranked by their sustainability score, whereby for every year the 25% best rated companies are assigned to the 1st quartile, the next 25% to the 2nd quartile, and so on. Based on this allocation, empirical transition probabilities from one of the four quartiles to any of the four quartiles after one year can be calculated.

1.3.3. Results of Markov Transition Matrices

From the average one-year transition probabilities in Table 1.2, it can be seen that the probability of staying in the current quartile is the highest and ranges from 47.53% for the 2nd quartile to 72.21% for the last quartile. Additionally, the probability decreases in the distance between two quartiles. Furthermore, the probability that a top-ranked firm will end up in the 4th quartile in the following year is only 0.37% and the probability of a "bad" company to be part of the first quartile in the following period is 1.23%.

Moreover, Markov transition matrices for every single year 2001–2007 were scrutinized. The results for the single years are quite similar to the average observation in Table 1.2. Finally, a six-year Markov transition matrix was computed. The results are shown in Table 1.3.

Nearly half of the companies that were ranked in the first quartile in 2001 were still in the first quartile in 2007. The probability that a highly sustainable company will be part of the worst quartile at the end of the six years is 5.36% and the probability of the opposite case, i.e., a "bad" company ending as a sustainability leader after six years, is 7.02%.

Table 1.2 Average One-Year Markov Transition Probabilities (Year 2001–2007).

		Next year quartile			
		1 (%)	2 (%)	3 (%)	4 (%)
Last year quartile	1	69.74	25.00	4.90	0.37
	2	23.83	47.53	24.35	4.29
	3	5.15	21.74	49.94	23.17
	4	1.23	5.96	20.60	72.21

Table 1.3 Markov Six-Year Transition Probabilities (Year 2001–2007).

		Next year quartile			
		1 (%)	2 (%)	3 (%)	4 (%)
Last year quartile	1	46.43	26.79	21.43	5.36
	2	25.00	39.29	32.14	3.57
	3	21.43	14.29	32.14	32.14
	4	7.02	19.30	14.04	59.65

Altogether, the results provide evidence to the assumption that sustainability rankings do not have a high degree of short-term variation.

1.4. SRI IN PORTFOLIO CONTEXT

After having analyzed the sustainability of sustainability in the preceding section, this section will scrutinize how SRI can be evaluated with regard to the portfolio context. The main questions to be answered are whether investors shall add SRI investments to their portfolio, and if so, with which weighting.

In the conducted portfolio case study, the SRI market is represented by the Advanced Sustainable Performance Index (ASPI). The ASPI is a European index consisting of 120 companies and is published by Vigeo Group, an extra-financial supplier and rating agency in the field of sustainable development and social responsibility (for further information see [13]). In order to include dividend payments to the analysis, total return indices are used, i.e., dividends are reinvested. This approach has two main advantages. First, the index already represents a selected basket of the asset category SRI and the time series are readily available. Second, the predefined index is widespread and thus has the advantage that the companies' specific risks are already eliminated by diversification. As a result, only the diversification effect of the asset class SRI itself is observed.

1.4.1. Description of the Dataset and Statistical Properties

The portfolio analysis is based on daily log-returns of the asset classes bonds (represented by the JP Morgan Global Government Bond Index), stocks (represented by the Dow Jones Total Markets World Index), and SRI (represented, as described above, by the ASPI index) between 1 January 1992 and 30 September 2008. The main empirical statistics are shown in Table 1.4.

Table 1.4 Empirical Statistics of Daily Log-Returns.

Empirical statistics	Bonds	Stocks	SRI
Mean	0.00024	0.00026	0.00038
Mean (annualized)	0.05917	0.06399	0.09425
Standard deviation	0.00389	0.00803	0.01216
Standard deviation (annualized)	0.06151	0.12702	0.19230
Skewness	−0.00619	−0.29037	−0.13149
Excess kurtosis	1.44597	4.11292	3.58599
Autocorrelation: lag 1	0.03266	0.16873	0.00494
Autocorrelation: lag 2	0.00386	−0.02818	−0.02391
Autocorrelation: lag 3	−0.01373	−0.02108	−0.06324
Autocorrelation of squared returns (lag 1)	0.03859	0.13695	0.19301
5% critical value for autocorrelation	0.03026	0.03026	0.03026

By comparing mean and standard deviation of bonds and stocks, it becomes evident that most of the risk–averse investors would invest the bulk of their wealth in bonds. This is due to the extremely high mean for bonds (5.92% per annum) combined with a low standard deviation. Additionally, bonds display the highest skewness and lowest excess kurtosis, which is generally preferred by risk–averse investors. As it is a debatable point whether past returns indicate the future in a sufficient way, experts' forecasts about expected returns are often used to solve this shortcoming. By using the Black–Litterman approach to adjust the empirical returns, the empirical mean μ_{emp} itself as well as absolute and relative forecasts are taken into account (see, e.g., [14]). This approach can be interpreted as a linear combination of these two components at a given confidence level τ regarding the forecasts. The Black–Litterman expectations μ_{BL} can be expressed by (given that L is invertible)

$$\mu_{\text{BL}} = \tau \cdot L^{-1}q + (1-\tau) \cdot \mu_{\text{emp}}, \tag{1.1}$$

where L represents the linear transformation $L\mu$ of the asset classes expected return vector μ and for each forecast, whose actual value is specified in q. The assumptions about the forecasts are taken from [15]. This means that the annual return of bonds is expected to be 3.96% and the equity risk premium amounts to 3.5%. The additional assumption that the difference of the means of stocks and SRI does not change leads to

$$L = \begin{pmatrix} 1 & 0 & 0 \\ -1 & 1 & 0 \\ 0 & -1 & 1 \end{pmatrix} \quad \text{and} \quad q = \begin{pmatrix} 0.0396/250 \\ 0.0350/250 \\ 0.0303/250 \end{pmatrix}.$$

For $\tau = 0$, the Black–Litterman expectations are equal to the empirical means, while $\tau = 1$ leads to expectations which are completely driven by the forecasts. Table 1.5 provides the Black–Litterman expectations for a confidence level of $\tau = 0.75$.

Table 1.5 Black–Litterman Expectations for Asset Class Log-Returns.

Black–Litterman expectations	Bonds	Stocks	SRI
Daily return	0.00018	0.00029	0.00041
Annual return	0.04449	0.07195	0.10221

Table 1.6 *P*-Values of Jarque–Bera and Ljung–Box-Q Tests.

Test	Null hypothesis	Bonds	Stocks	SRI
Jarque–Bera	Normal distribution	*<0.001*	*<0.001*	*<0.001*
Ljung–Box-Q (Q1)	No autocorrelation (up to lag 1)	*0.0308*	*0*	0.7438
Ljung–Box-Q (Q2)	No autocorrelation (up to lag 2)	0.0940	*0*	0.2715
Ljung–Box-Q (Q3)	No autocorrelation (up to lag 3)	0.1354	*0*	*0.0002*
Ljung–Box-Q (QS1)	No ac. (squared returns, lag 1)	*0.0096*	*0*	*0*

The empirical returns are adjusted for the Black–Litterman expectations by applying a linear shift to the whole dataset. Hence, all other empirical statistics (except for the autocorrelation in squared returns) are unaffected.

Skewness and excess kurtosis in Table 1.4 lead to the presumption that the returns of all three asset classes are non-normally distributed. To test for non-normality and autocorrelation, a Jarque–Bera test and a Ljung–Box-Q test (see [16] and [17]) were applied. The *p*-values of both tests are given in Table 1.6. Italicised values are those smaller than 0.05, for which the null hypothesis can be rejected at a significance level of 5%.

As correlations are essential for diversification in a portfolio context, the correlations of the empirical daily log-returns are listed in Table 1.7. The high correlation between stocks and SRI is in line with the findings of [12]. One reason for this fact may be that SRI stocks are simply a subset of the whole stock universe. Nevertheless, each correlation coefficient smaller than one allows to benefit from diversification.

Table 1.7 Empirical Correlations of Daily Log-Returns.

Correlation	Bonds	Stocks	SRI
Bonds	1	−0.034524	0.044066
Stocks	−0.034524	1	0.732227
SRI	0.044066	0.732227	1

1.4.2. Markov-Switching Model

Due to the described non-normality and autocorrelation of the considered time series of daily log-returns, the standard Black–Scholes model, which implies i.i.d. normally distributed log-returns, is not appropriate to describe the asset returns. As Markov-Switching models allow for non-normality and autocorrelation at the same time, this model class is applied in this study. To be more precise, a state-independent (first lag) autoregressive Markov-Switching model as introduced in [18] is utilized. Further applications of Markov-Switching models in a portfolio context can, e.g., be found in [15] or [19].

It is assumed throughout that the return of asset class $a \in \{1, 2, 3\}$ at time t is given by

$$r_{t,a} = \mu_{s_t,a} + \phi_a \cdot (r_{t-1,a} - \mu_{s_{t-1},a}) + \epsilon_{t,a}, \tag{1.2}$$

where s_t indicates the state of the markets at time t, $\mu_{s_t,a}$ denotes the mean return of the asset class a in state s_t. Here, $a = 1$ corresponds to the asset class bonds, $a = 2$ to stocks, and $a = 3$ to the SRI asset class. Furthermore, $\epsilon_t = (\epsilon_{t,1}, \epsilon_{t,2}, \epsilon_{t,3})^T$ represents the innovation at time t with $\epsilon_t \sim N(0, \Sigma_{s_t})$ and ϕ_a the autocorrelation parameter for asset class a satisfying $|\phi_a|<1$.

The Markov-Switching model allows the market to be in two different regimes ($s_t = 1$ for state 1 and $s_t = 2$ for state 2). For the reasons adduced in [15], only two meta states are allowed. As a result, all three assets are in the same state at each point of time t. Changes between the two states over time are modeled by a Markov chain with transition probabilities given by the matrix

$$P = \begin{pmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{pmatrix},$$

where $P(s_t = j|s_{t-1} = i) = p_{ij}$.

Therefore, the whole process is parametrized by a vector

$$\theta = (\mu_1, \mu_2, p_{12}, p_{21}, \phi, \Sigma_1, \Sigma_2)$$

with $\mu_1, \mu_2 \in \mathbb{R}^3, \phi \in [-1, 1]^3, p_{12}, p_{21} \in [0, 1]$, and $\Sigma_1, \Sigma_2 \in \mathbb{R}^{3\times 3}$. The assumption of only two meta states has the great advantage that overfitting problems can be avoided.

1.4.3. Fitting the Model Parameters

The model parameters are fitted in a way that the empirical moments equal the moments of the Markov-Switching process best possible. The applied method of moments is described in detail in [18]. With regard to the empirical statistics, the focus of the fitting lies on the first four moments and the autocorrelation of lag 1. The resulting parameters and transition probabilities are displayed in Table 1.8.

Table 1.8 Markov-Switching Model Parameters.

Parameter	μ_1	μ_2	σ_1	σ_2	ϕ	p_{12}	p_{21}
Bonds	0.00018	0.00015	0.00325	0.00630	0.03270		
Stocks	0.00062	−0.00108	0.00519	0.01473	0.16550	0.0579	0.2425
SRI	0.00064	−0.00055	0.00812	0.02166	0.00389		

The parameters allow for the derivation of crucial information about the two possible meta states. State 1 characterizes a bull market for all three assets. The expected return of stocks and SRI is almost the same (15.4% p.a. for stocks and 16% p.a. for SRI) whereas the standard deviation is much higher for SRI. In state 2, the expected return of bonds only suffers a small decline compared to state 1 (from 4.6% p.a. to 3.8% p.a.) but the volatility nearly doubles in this regime. For stocks and SRI state 2 resembles a bearish market with huge losses for both asset classes (−26.9% p.a. for stocks and −13.9% p.a. for SRI) and high standard deviations. The observation of an increasing volatility in falling markets can be found in empirical studies like [20]. The transition probabilities p_{12} and p_{21} of the Markov chain imply a realistic stability of the two possible states. If the market is in a bullish or a bearish scenario respectively, the market remains in the current state on the following day with a high probability.

As the fitting is based on minimizing the sum of squared deviations between the empirical and theoretical statistics, these are outlined in Table 1.9.

The close match is emphasized by the theoretical correlations of the model, which fit the empirical correlations very well (compare Tables 1.7 and 1.10).

It is worthwhile to have a look at the correlation structures of the error terms ϵ_t, which are depicted in Table 1.11. The correlation of the error terms between stocks and SRI is about 0.9 in the “bad” state (state 2) and thus much higher than in the “good” state (state 1) with about 0.47.

Table 1.9 Empirical and Theoretical Statistics of Daily Log-Returns.

Statistics		Mean	Std. dev.	Skewness	Ex. kurt.	Autocorr.
Bonds	Empirical	0.0001780	0.003890	−0.006192	1.445971	0.032663
	Theoretical	0.0001777	0.004020	−0.006200	1.517654	0.032703
Stocks	Empirical	0.0002878	0.008033	−0.290370	4.112919	0.168726
	Theoretical	0.0002890	0.008109	−0.287749	4.122927	0.169116
SRI	Empirical	0.0004088	0.012162	−0.131494	3.585990	0.004943
	Theoretical	0.0004100	0.011994	−0.130343	3.680593	0.004961

Table 1.10 Theoretical Correlations of Daily Log-Returns.

Correlation	Bonds	Stocks	SRI
Bonds	1	−0.033037	0.043037
Stocks	−0.033037	1	0.733543
SRI	0.043037	0.733543	1

Table 1.11 Correlation Structure of Error Terms in States 1 and 2.

Correlation	Bonds	Stocks	SRI
	State 1		
Bonds	1	−0.264006	−0.414615
Stocks	−0.264006	1	0.467326
SRI	−0.414615	0.467326	1
	State 2		
Bonds	1	0.140301	0.414109
Stocks	0.140301	1	0.896169
SRI	0.414109	0.896169	1

1.4.4. Simulation of Returns

The portfolio optimization case study will be based on the distribution of simulated returns according to the model in Sec. 1.4.2. Therefore, a Monte Carlo simulation with 20,000 return paths is conducted. Each path consists of 1250 returns and represents, assuming 250 trading days per year, five years of data for each asset class. The initial state of the underlying Markov chain is drawn from the stationary distribution $\pi = (\pi_1, 1 - \pi_1)$ with $\pi_1 = p_{21}/(p_{12} + p_{21})$.

Due to non-normality and the importance of skewness and kurtosis with respect to the risk aversion of an investor (risk–averse investors have a positive preference direction for skewness and a negative one for excess kurtosis), it is necessary to introduce more complex portfolio concepts compared to a pure mean–variance optimization.

1.4.5. Portfolio Optimization Models

Having deduced the distributions of the simulated return paths, five different models are applied in order to optimize the investor's portfolio. Two constraints for the portfolio weights x ensure a full investment of the available budget ($\sum_{i=1}^{3} x_i = 1$), and avoid short-selling ($x_i \geq 0, i = 1, 2, 3$).

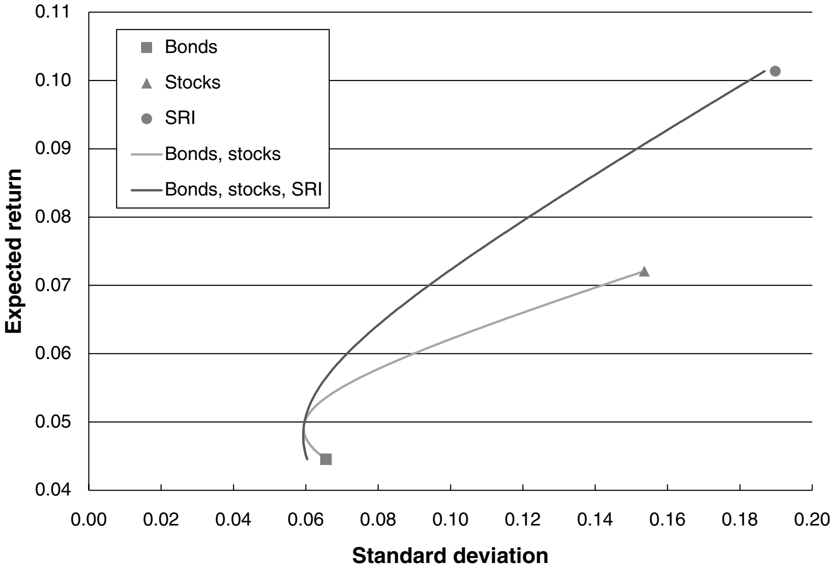


Figure 1.1 Efficient frontier for one-year time horizon.

The traditional mean–variance framework based on [21] only takes the first two moments of the return distribution into account. It is defined by

$$\max_x x^T \mu - \frac{\lambda}{2} x^T \Sigma x, \tag{1.3}$$

where μ denotes the vector of expected asset returns, Σ the return covariance–matrix, and λ the risk–aversion parameter of the investor.

Figure 1.1 shows the diversification effect which can be obtained by including the asset SRI into an existing portfolio of bonds and stocks.

Due to the importance of higher moments within the portfolio context, the power-utility model and frameworks which maximize different performance measures are introduced in the following.

The power-utility model is defined by the optimization problem

$$\max_x \mathbb{E}[U(R(x))] = \begin{cases} \max\limits_x \mathbb{E}[\gamma^{-1}(1 + R(x))^{\gamma}], & \gamma < 1 \wedge \gamma \neq 0 \\ \max\limits_x \mathbb{E}[\ln(1 + R(x))], & \gamma = 0 \end{cases}, \tag{1.4}$$

where γ describes the risk aversion of the investor and $R(x)$ is the portfolio return depending on the portfolio weights x.

The third optimization model maximizes the performance measure Ω introduced in [22]. In this framework, each investor can set a threshold to classify the returns into gains (returns above the threshold) and losses (returns below the threshold). Ω is defined as the ratio of probability-weighted gains to losses and thus equal to the upside potential divided by the downside potential. The corresponding optimization problem is given by

$$\max_x \Omega_\tau(R(x)) = \max_x \frac{\mathbb{E}[R(x) - \tau]^+}{\mathbb{E}[\tau - R(x)]^-}, \tag{1.5}$$

where τ is the loss threshold and $R(x)$ the portfolio return for portfolio weights x.

The performance measure Score-value considers the difference of upside and downside potential. The risk-free rate r is used as threshold and the downside potential is weighted with a risk–aversion parameter λ_{Sc}. This leads to an optimization problem defined by

$$\max_x \text{Score}_{\lambda_{Sc}}(R(x)) = \max_x \mathbb{E}[R(x) - r]^+ - \lambda_{Sc} \cdot \mathbb{E}[r - R(x)]^-. \tag{1.6}$$

The Mean-Conditional Value at Risk (MCVaR) is a risk measure referring to the tail of a distribution. It is based on the Conditional Value at Risk (CVaR) defined by

$$CVaR(R(x)) = \mathbb{E}[R(x)|R(x) < VaR(R(x))], \tag{1.7}$$

where $VaR(R(x))$ is the Value at Risk (see, e.g., [23]) of the portfolio return $R(x)$ at a given confidence level α (in the case under consideration $\alpha = 99.5\%$). In order to consider both risk and return, the optimization problem is given by

$$\max_x MCVaR_{\lambda_{MCVaR}}(R(x)) = \max_x \mathbb{E}[R(x)] - \lambda_{MCVaR} CVaR(R(x)) \tag{1.8}$$

with λ_{MCVaR} denoting the respective risk–aversion parameter.

1.4.6. Definition of Investor Types

All optimization models introduced above take different levels of risk–aversion into account. To consistently define investor types over the different models, the risk–aversion parameters are chosen such that they result in the same optimal asset allocations in a world where only stocks and bonds exist (see, e.g., [19]). In this case study, three investor types with different levels of risk aversion are used. They are represented by their characteristic benchmark portfolios with bonds:stocks equal to 0.7:0.3 (Investor A), 0.5:0.5 (Investor B), and 0.3:0.7 (Investor C). For the one-year time horizon, the respective parameters are given in Table 1.12.

1.4.7. Optimal Portfolios

Using the risk–aversion parameters of the three different investor types, optimal portfolios of bonds, stocks, and SRI are constructed. The optimization is conducted for all introduced frameworks with time horizons of one, three, and five years. As the results are quite similar for all three time horizons, only the results of the one-year horizon

Table 1.12 Risk–Aversion Parameters for the Three Investor Types (One Year).

Risk aversion	λ	γ	τ	λ_{Sc}	λ_{MCVaR}
Investor *A*	7.0609	−6.9009	0.0245	3.0632	0.1957
Investor *B*	2.8570	−2.8353	0.0390	1.8072	0.0983
Investor *C*	1.7908	−1.7820	0.0427	1.6328	0.0768

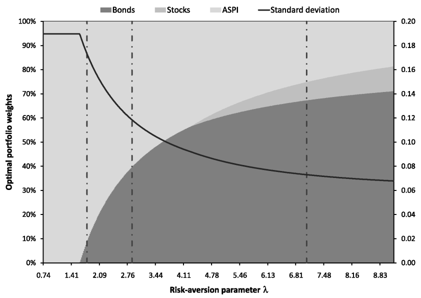
Table 1.13 Weights and Performance Measures of Optimal Portfolios (One Year).

Framework		MV	PU	Omega	Score	MCVaR
		Portfolio weights				
	Bonds	0.6735	0.6732	0.6605	0.6252	0.6169
A	Stocks	0.0759	0.0722	0.0624	0.0360	0.0376
	SRI	0.2506	0.2546	0.2771	0.3388	0.3455
	Bonds	0.3968	0.3955	0.3832	0.0000	0.0000
B	Stocks	0.0000	0.0000	0.0000	0.0000	0.0000
	SRI	0.6032	0.6045	0.6168	1.0000	1.0000
	Bonds	0.0940	0.0927	0.1114	0.0000	0.0000
C	Stocks	0.0000	0.0000	0.0000	0.0000	0.0000
	SRI	0.9060	0.9073	0.8886	1.0000	1.0000
		Risk and performance measures				
	Sharpe	0.3542	0.3547	0.3586	0.3663	0.3671
A	Omega	3.5017	3.5026	3.5055	3.4881	3.4828
	Score	−0.0112	−0.0112	−0.0110	−0.0107	−0.0107
	MCVaR	0.0329	0.0330	0.0331	0.0333	0.0333
	Sharpe	0.3693	0.3693	0.3687	0.3497	0.3497
B	Omega	2.3309	2.3309	2.3310	2.2879	2.2879
	Score	0.0208	0.0209	0.0211	0.0285	0.0285
	MCVaR	0.0545	0.0545	0.0547	0.0605	0.0605
	Sharpe	0.3540	0.3540	0.3549	0.3497	0.3497
C	Omega	2.1796	2.1796	2.1796	2.1779	2.1779
	Score	0.0342	0.0342	0.0337	0.0366	0.0366
	MCVaR	0.0673	0.0673	0.0669	0.0695	0.0695

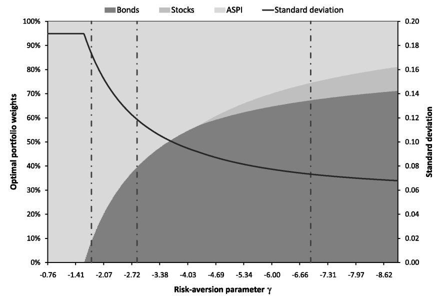
are presented in detail here. Table 1.13 shows the optimal portfolio weights as well as the computed performance measures Ω, Score-value, MCVaR, and Sharpe ratio. The first three were already introduced in Sec. 1.4.5. The well-known Sharpe ratio measures the expected excess return over the riskless investment in units of standard deviation (see [24]). The low risk–averse Investor C invests largely into SRI. In the mean-variance (MV), the power-utility (PU), and the Omega framework, he allocates around 90% into SRI and in the Score-value and the MCVaR framework he is completely invested in SRI. As Investor C does not invest in stocks at all, the remainder of his wealth is invested in bonds. The strategy of Investor B is very similar with the only difference being that the portfolio weights of the asset class SRI are smaller in the MV, PU, and Omega framework. The best diversified portfolios are held by the highly risk–averse Investor A. Most of his wealth — between 61% and 68% — is invested into bonds. The majority of the remainder is allocated to SRI, leading to a fraction of 25–35% and only a small amount is invested into stocks (between 3–8%). Overall, the results emphasize that SRI can be interpreted as a substitute for stocks and that only the most risk–averse investor allocates money to the substituted asset class in order to benefit from the diversification effect.

Figures 1.2 (a)–(e) illustrate the portfolio allocations in dependence of the respective risk–aversion parameter. The vertical lines indicate the three considered investor types. The solid line displays the risk of the portfolios measured by the standard deviation of the portfolios' returns. As mentioned above, the proportion invested into stocks is due to the substitution effect always very small or even zero. A further interesting issue is the development of the proportion invested into bonds. In the MV, PU, and Omega framework, the fraction of bonds increases slowly with increasing risk–aversion whereas it ascends late but steeply in the Score-value and the MCVaR framework what results in an enormous reduction of risk from that point on.

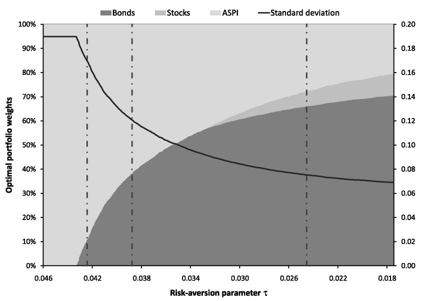
In order to get more information about the substitution effect, a sensitivity analysis is performed for the mean–variance framework with a one-year time horizon. As only the most risk–averse investor allocates parts of his wealth to stocks, the question arises under which circumstances the less risk–averse Investor C mixes stocks into his portfolio. For this purpose, the Black–Litterman expectation for the annual return of SRI is gradually decreased, starting from a value of 10.22% (see Table 1.5). With the help of the overall probability π_1 (see Sec. 1.4.4) the amount of reduction Δ can be split up for the two regimes. For state 1 the reduction is $\pi_1 \cdot \Delta$ and for state 2 it equals $(1 - \pi_1) \cdot \Delta$. While facing the same risk exposure, the upper hurdle rate for the expected return is determined by a value of 9.27%. This value represents the highest expected return of SRI for which Investor C still invests a small amount into stocks. A further decrease of the expected return leads to a partial replacement of SRI by stocks. The lower hurdle rate is given by an annual SRI return of 7.01%, i.e., if the expected return is below the lower hurdle rate Investor C will not invest in SRI anymore and therefore create the appropriate benchmark portfolio of 70% stocks and 30% bonds.



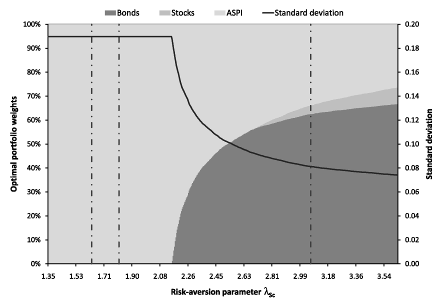
(a) MV framework.



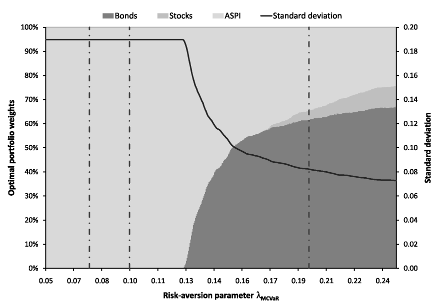
(b) PU framework.



(c) Omega framework.



(d) Score value framework



(e) MCVaR framework.

Figure 1.2 Optimal portfolio weights in different optimization frameworks.

1.5. CONCLUSION

SRI is a growing asset class. By analyzing SAM sustainability scores, it was shown that an SRI portfolio has a high degree of consistency, i.e., sustainable companies are likely to stay sustainable in the future. For the best ranked companies, the probability of being in the 1st quartile again in the next year is 70% on average. Moreover, optimal portfolios for different investor types are constructed. The parameter estimates of the underlying Markov-Switching model are based on a time series ranging from 1992 to 2008. The main finding of the conducted case study is that SRI turns out to be a substitute for stocks and that the less risk–averse an investor is the more he invests in SRI, respectively, does a full investment into this asset class. More risk–averse investors use all three asset classes in order to gain from diversification effects. Nevertheless, only a very small fraction ($<8\%$) is invested into stocks.

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