Handbook of Sustainable Finance

Thierry Roncalli
Université Paris-Saclay
# Contents

**Contents** vii  
**Preface** ix  
**List of Symbols and Notations** xi  
**Abbreviations** xvii  

## 1 Introduction  
1.1 Definition 1  
1.2 Short history of responsible and ethical investing 2  
1.3 The ESG ecosystem 6  
  1.3.1 Sustainable investment forum 7  
  1.3.2 Initiatives 7  
  1.3.3 Regulators 13  
  1.3.4 Reporting frameworks 17  
  1.3.5 Rating agencies and data providers 24  
1.4 Regulatory framework 27  
  1.4.1 EU taxonomy regulation 30  
  1.4.2 Climate benchmarks 34  
  1.4.3 Sustainable finance disclosure regulation 35  
  1.4.4 MiFID II and sustainable preferences 36  
  1.4.5 Corporate sustainability reporting directive 37  
1.5 The market of ESG investing 38  
  1.5.1 ESG strategies 38  
  1.5.2 The market share of ESG investing 41  
1.6 Conclusion 44

## I ESG Risk 45

## 2 ESG Scoring 47  
2.1 Data and variables 48  
  2.1.1 Sovereign ESG data 48  
  2.1.2 Corporate ESG data 59  
2.2 Scoring system 69  
  2.2.1 A primer on scoring theory 70  
  2.2.2 Tree-based scoring methods 71
2.2.3 Other statistical methods .................................... 89
2.2.4 Performance evaluation criteria ................................. 90

2.3 Rating system .......................................................... 104
2.3.1 Definition ............................................................... 104
2.3.2 ESG rating process .................................................. 105
2.3.3 Rating migration matrix ............................................. 109
2.3.4 Comparison with credit ratings ................................. 123

2.4 Exercises ................................................................. 124
2.4.1 Score normalization when the features are independent ..... 124
2.4.2 Score normalization when the features are correlated ........ 126
2.4.3 Construction of a sovereign ESG score ....................... 126
2.4.4 Probability distribution of an ESG score ..................... 126
2.4.5 Markov generator of ESG migration matrix ................. 128
2.4.6 Properties of Markov chains .................................... 128

3 Impact of ESG Investing on Asset Prices and Portfolio Returns 129
3.1 Theoretical models ..................................................... 130
3.1.1 A primer on modern portfolio theory ......................... 130
3.1.2 ESG risk premium .................................................. 143
3.1.3 ESG efficient frontier .............................................. 161

3.2 Empirical results ....................................................... 170
3.2.1 Equity markets ...................................................... 170
3.2.2 Fixed-income markets ............................................. 191
3.2.3 Cost of capital ....................................................... 200

3.3 Strategic asset allocation ............................................ 200

3.4 Exercises ................................................................. 201
3.4.1 Equity portfolio optimization with ESG scores .............. 201
3.4.2 Bond portfolio optimization with ESG scores ............... 202
3.4.3 Minimum variance portfolio with climate risk .............. 202
3.4.4 Cost of capital and green sentiment ......................... 202
3.4.5 Strategic asset allocation with ESG preferences .......... 202

4 Sustainable Financial Products ........................................ 203
4.1 The market of ESG mutual funds .................................. 203
4.1.1 Greenwashing issues .............................................. 203
4.1.2 Classification of ESG investment funds ...................... 203
4.1.3 The case of index funds .......................................... 203
4.1.4 Market growth statistics ........................................ 203
4.2 Green and social bonds .............................................. 204
4.2.1 Green bonds ......................................................... 205
4.2.2 Social bonds ........................................................ 217
4.2.3 Other sustainability-related instruments .................... 219
4.3 Sustainable real assets ............................................... 222
4.3.1 Green infrastructure .............................................. 222
4.3.2 Green real estate .................................................. 222
4.3.3 ESG private equity and debt funds ......................... 222

Handbook of Sustainable Finance
<table>
<thead>
<tr>
<th>Section</th>
<th>Title</th>
<th>Pages</th>
</tr>
</thead>
<tbody>
<tr>
<td>5</td>
<td>Impact Investing</td>
<td>223</td>
</tr>
<tr>
<td>5.1</td>
<td>Definition</td>
<td>223</td>
</tr>
<tr>
<td>5.2</td>
<td>Thematic funds</td>
<td>223</td>
</tr>
<tr>
<td>5.3</td>
<td>Measurement tools</td>
<td>223</td>
</tr>
<tr>
<td>5.4</td>
<td>An example with the biodiversity risk</td>
<td>223</td>
</tr>
<tr>
<td>6</td>
<td>Engagement &amp; Voting Policy</td>
<td>225</td>
</tr>
<tr>
<td>6.1</td>
<td>Active ownership</td>
<td>226</td>
</tr>
<tr>
<td>6.1.1</td>
<td>Definition</td>
<td>226</td>
</tr>
<tr>
<td>6.1.2</td>
<td>The various forms of active ownership</td>
<td>227</td>
</tr>
<tr>
<td>6.1.3</td>
<td>Individual versus collaborative engagement</td>
<td>239</td>
</tr>
<tr>
<td>6.1.4</td>
<td>The role of institutional investors</td>
<td>239</td>
</tr>
<tr>
<td>6.1.5</td>
<td>Impact of active ownership</td>
<td>239</td>
</tr>
<tr>
<td>6.2</td>
<td>ESG voting</td>
<td>240</td>
</tr>
<tr>
<td>6.2.1</td>
<td>Voting process</td>
<td>240</td>
</tr>
<tr>
<td>6.2.2</td>
<td>Proxy voting</td>
<td>240</td>
</tr>
<tr>
<td>6.2.3</td>
<td>Defining a voting policy</td>
<td>240</td>
</tr>
<tr>
<td>6.2.4</td>
<td>Statistics about ESG voting</td>
<td>241</td>
</tr>
<tr>
<td>7</td>
<td>Extra-financial Accounting</td>
<td>249</td>
</tr>
<tr>
<td>7.1</td>
<td>Historical perspectives</td>
<td>249</td>
</tr>
<tr>
<td>7.2</td>
<td>Single vs. double materiality</td>
<td>249</td>
</tr>
<tr>
<td>7.3</td>
<td>Environmental accounting</td>
<td>249</td>
</tr>
<tr>
<td>7.3.1</td>
<td>National environmental accounts</td>
<td>249</td>
</tr>
<tr>
<td>7.3.2</td>
<td>Corporate environmental accounts</td>
<td>249</td>
</tr>
<tr>
<td>7.4</td>
<td>Sustainability accounting</td>
<td>249</td>
</tr>
<tr>
<td>7.4.1</td>
<td>Social issues</td>
<td>249</td>
</tr>
<tr>
<td>7.4.2</td>
<td>Governance factors</td>
<td>249</td>
</tr>
<tr>
<td>II</td>
<td>Climate Risk</td>
<td>251</td>
</tr>
<tr>
<td>8</td>
<td>The Physics and Economics of Climate Change</td>
<td>253</td>
</tr>
<tr>
<td>8.1</td>
<td>Awareness of climate change impacts</td>
<td>254</td>
</tr>
<tr>
<td>8.1.1</td>
<td>Scientific evidence of global warming</td>
<td>254</td>
</tr>
<tr>
<td>8.1.2</td>
<td>From the Holocene to the Anthropocene?</td>
<td>264</td>
</tr>
<tr>
<td>8.1.3</td>
<td>The physics of climate change</td>
<td>299</td>
</tr>
<tr>
<td>8.2</td>
<td>The ecosystem of climate change</td>
<td>316</td>
</tr>
<tr>
<td>8.2.1</td>
<td>Scientists</td>
<td>316</td>
</tr>
<tr>
<td>8.2.2</td>
<td>Conferences of the parties</td>
<td>316</td>
</tr>
<tr>
<td>8.2.3</td>
<td>Regulation policies</td>
<td>316</td>
</tr>
<tr>
<td>8.3</td>
<td>Integrated assessment models</td>
<td>317</td>
</tr>
<tr>
<td>8.3.1</td>
<td>The DICE model</td>
<td>317</td>
</tr>
<tr>
<td>8.3.2</td>
<td>Other models</td>
<td>341</td>
</tr>
<tr>
<td>8.3.3</td>
<td>Scenarios</td>
<td>348</td>
</tr>
<tr>
<td>8.4</td>
<td>Environmentally-extended input-output model</td>
<td>374</td>
</tr>
<tr>
<td>8.4.1</td>
<td>Input-output analysis</td>
<td>374</td>
</tr>
<tr>
<td>8.4.2</td>
<td>Application to environmental problems</td>
<td>386</td>
</tr>
</tbody>
</table>
8.4.3 Estimation of first-tier and indirect emissions 390
8.4.4 Imported and exported carbon emissions 403
8.4.5 Taxation, pass-through and price dynamics 413
8.5 Exercises 434

9 Climate Risk Measures 435
9.1 Carbon emissions 436
  9.1.1 Global warming potential 436
  9.1.2 Consolidation accounting at the company level 442
  9.1.3 Scope 1, 2 and 3 emissions 444
  9.1.4 Carbon emissions of investment portfolios 460
  9.1.5 Statistics 462
  9.1.6 Negative and avoided emissions 465
9.2 Carbon intensity 467
  9.2.1 Physical intensity ratios 467
  9.2.2 Monetary intensity ratios 468
  9.2.3 Statistics 471
9.3 Dynamic risk measures 474
  9.3.1 Carbon budget 474
  9.3.2 Carbon trend 480
  9.3.3 Participation, ambition and credibility for an alignment strategy 489
  9.3.4 Illustration 494
9.4 Greenness measures 498
  9.4.1 Green taxonomy 498
  9.4.2 Green revenue share 499
  9.4.3 Green capex 502
  9.4.4 Green-to-brown ratio 502
  9.4.5 Other metrics 502
9.5 Exercises 502
  9.5.1 Stochastic modeling of global warming potentials 502
  9.5.2 Calculation of global temperature potentials 502

10 Transition Risk Modeling 503
10.1 Carbon tax 504
  10.1.1 Mathematics of carbon tax 504
  10.1.2 Abatement cost 504
10.2 Stranded assets 505
10.3 Decarbonization pathway 505
10.4 Transition risk measures 505
10.5 Temperature rating modeling 505
10.6 Exercises 505

11 Climate Portfolio Construction 507
11.1 Portfolio optimization in practice 508
  11.1.1 Equity portfolios 508
  11.1.2 Bond portfolios 514
  11.1.3 Advanced optimization problems 521
11.2 Portfolio decarbonization 527
### Contents

<table>
<thead>
<tr>
<th>Section</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>A.2.3 Estimation methods</td>
<td>600</td>
</tr>
<tr>
<td>A.3 Stochastic analysis</td>
<td>610</td>
</tr>
<tr>
<td>A.3.1 Stochastic optimal control</td>
<td>610</td>
</tr>
<tr>
<td>A.3.2 Jump-diffusion processes</td>
<td>610</td>
</tr>
<tr>
<td>A.4 Spatial data</td>
<td>610</td>
</tr>
<tr>
<td>A.4.1 Spherical coordinates</td>
<td>610</td>
</tr>
<tr>
<td>A.4.2 Geographic coordinate systems</td>
<td>610</td>
</tr>
<tr>
<td>A.4.3 Network common data form</td>
<td>610</td>
</tr>
<tr>
<td>B Solutions to the Tutorial Exercises</td>
<td>611</td>
</tr>
<tr>
<td>B.1 Exercises related to ESG risk</td>
<td>611</td>
</tr>
<tr>
<td>B.1.1 Score normalization when the features are independent (Exercise 2.4.1)</td>
<td>611</td>
</tr>
<tr>
<td>B.1.2 Score normalization when the features are correlated (Exercise 2.4.2)</td>
<td>611</td>
</tr>
<tr>
<td>B.1.3 Construction of a sovereign ESG score (Exercise 2.4.3)</td>
<td>611</td>
</tr>
<tr>
<td>B.1.4 Probability distribution of ESG scores (Exercise 2.4.4)</td>
<td>611</td>
</tr>
<tr>
<td>B.1.5 Markov generator of ESG migration matrix (Exercise 2.4.5)</td>
<td>621</td>
</tr>
<tr>
<td>B.1.6 Properties of Markov chains (Exercise 2.4.6)</td>
<td>621</td>
</tr>
<tr>
<td>B.1.7 Equity Portfolio optimization with ESG scores (Exercise 3.5.1)</td>
<td>622</td>
</tr>
<tr>
<td>B.1.8 Bond portfolio optimization with ESG scores (Exercise 3.5.2)</td>
<td>631</td>
</tr>
<tr>
<td>B.1.9 Minimum variance portfolio with climate risk (Exercise 3.5.3)</td>
<td>631</td>
</tr>
<tr>
<td>B.1.10 Cost of capital and green sentiment (Exercise 3.5.4)</td>
<td>631</td>
</tr>
<tr>
<td>B.1.11 Strategic asset allocation with ESG preferences (Exercise 3.5.5)</td>
<td>631</td>
</tr>
<tr>
<td>B.1.12 Computation of the greenium computing (Exercise 4.6.1)</td>
<td>631</td>
</tr>
<tr>
<td>B.1.13 Dependence modeling of ESG and credit ratings (Exercise 4.6.2)</td>
<td>631</td>
</tr>
<tr>
<td>B.2 Exercises related to climate risk</td>
<td>632</td>
</tr>
<tr>
<td>B.2.1 Computing the carbon risk contribution in input-output matrix models (Exercise 8.4.1)</td>
<td>632</td>
</tr>
<tr>
<td>B.2.2 Computing the carbon tax in a two-period model (Exercise 8.4.2)</td>
<td>632</td>
</tr>
<tr>
<td>B.2.3 Probability distribution of carbon momentum (Exercise 9.5.1)</td>
<td>632</td>
</tr>
<tr>
<td>B.2.4 Carbon trajectory denoising (Exercise 9.5.2)</td>
<td>632</td>
</tr>
<tr>
<td>B.2.5 Computing the optimal carbon price in ETS (Exercise 10.4.1)</td>
<td>632</td>
</tr>
<tr>
<td>B.2.6 Equity and bond portfolio optimization with green preferences (Exercise 11.3.1)</td>
<td>633</td>
</tr>
<tr>
<td>B.2.7 Monotonicity property of the order-statistic and naive approaches (Exercise 11.3.2)</td>
<td>645</td>
</tr>
<tr>
<td>B.2.8 Dynamic optimization with noisy carbon footprints (Exercise 11.3.3)</td>
<td>645</td>
</tr>
<tr>
<td>B.2.9 Portfolio optimization with net zero metrics (Exercise 11.3.4)</td>
<td>645</td>
</tr>
<tr>
<td>B.2.10 Taxonomy-based optimization (Exercise 11.3.5)</td>
<td>645</td>
</tr>
<tr>
<td>B.2.11 Upper bound of taxonomy-based diversified portfolios (Exercise 11.3.6)</td>
<td>645</td>
</tr>
<tr>
<td>B.2.12 Minimum variance portfolios with transition risks (Exercise 11.3.7)</td>
<td>645</td>
</tr>
<tr>
<td>B.2.13 Extreme value theory applied to flooding (Exercise 12.5.1)</td>
<td>645</td>
</tr>
<tr>
<td>B.2.14 Modeling the dependence of physical risks with copula functions (Exercise 12.5.2)</td>
<td>645</td>
</tr>
<tr>
<td>B.2.15 Impact of the carbon tax in the default barrier (Exercise 13.4.1)</td>
<td>645</td>
</tr>
</tbody>
</table>

### Bibliography

<table>
<thead>
<tr>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>647</td>
</tr>
</tbody>
</table>

### Subject Index

<table>
<thead>
<tr>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>675</td>
</tr>
</tbody>
</table>
Author Index
Preface

Teaching sustainable finance

I started teaching finance at the University of Bordeaux in 1995. My first course was called Stochastic Finance and was dedicated to option pricing and stochastic calculus. At that time I was also working as a consultant for a bank to develop numerical methods for some exotic payoffs. I realized that this academic course could benefit from this professional position. Indeed, I learnt that the main problem of traders is not the calculation of the option price, but the definition of the hedging strategy. Combining academic theory with professional practice has been a constant theme of my teaching career. In the 2000s, my risk management courses made extensive use of the risk management knowledge acquired at the Groupe de Recherche Opérationnelle (GRO) at Crédit Lyonnais and Crédit Agricole between 1999 and 2005. In the 2010s, my courses in asset management were largely based on the professional experience developed at SGAM AI and Lyxor Asset Management between 2005 and 2016. This sustainable finance course follows the same path. It is largely based on the ESG and climate investing research I have conducted at Amundi Asset Management since 2018.

Although this course has many features in common with the previous ones, sustainable finance is not as mature as option pricing, risk management and asset management. In particular, regulation is in its infancy and not yet stabilised, academic models are still in their infancy, data are noisy, biased and of poor quality, and even concepts are not well defined. In this context, all actors (investors, issuers, financial institutions, regulators, etc.) are adopting a learning-by-doing approach. This has important implications for the development of a training course. Each year, the course needs to be updated by incorporating new advances in modelling, adjusting definitions, changing the structure of the lecture notes, removing obsolete sections and adding new paragraphs. Since its inception, the course has been a continuous work in progress.

The issue of sustainable economic growth is a major change in the way economics and finance are taught. However, most academic models do not take climate change into account because they were developed in the 19th and 20th centuries. Taking climate change into account requires a complete overhaul of economic theory and many related concepts: economic growth, negative externality, moral hazard, labour productivity, economic rationality, consumption maximization, social welfare, Pareto optimality, invisible hand, market efficiency, utility function, homo economicus, capital allocation, risk theory, golden rule, overlapping generations model, steady state, non-cooperative games, etc. As teachers, it is difficult to adapt to this new world because we lack distance and cannot benefit from well-established textbooks. However, we cannot wait as time is running out. Therefore, we have a heavy responsibility to educate students about these important issues without adequate tools and a normative framework. This explains why there are thousands of ways to teach sustainable finance. It is not a science. Then be careful about the content, because it necessarily reflects our personal beliefs and experiences. And so I claim the right to be biased.
About these lecture notes

In January 2019, I started to introduce some elements of ESG and climate investing in my course Advanced Asset Management. At that time, it was only about portfolio optimisation with ESG scores and carbon footprints. Over the years, the part dedicated to sustainable finance has increased and now makes up 25% of the course. In 2021, we had some discussions at the University of Paris-Saclay about the future development of the Masters in Finance. We decided to create a full and comprehensive course in sustainability finance, going beyond portfolio allocation. For the 2021/2022 academic year, I then put together a set of 770 slides for the first course at Paris-Saclay University. During the year, Peter Tankov also offered to share his course Green Finance at ENSAE Paris. At the same time, Emmanuel Gobet and Gilles Pagès proposed that I create a mathematical course on sustainable finance in the Master of Probability & Finance at Sorbonne University. Today, sustainable finance is taught in four master’s programmes: Master in Risk and Asset Management (Paris-Saclay University), Master in Banking & Finance (Paris-Saclay University), Master in Statistics, Finance and Actuarial Science (ENSAE Paris and Paris Cité University) and Master in Probability & Finance (Sorbonne University). These four courses differ in the number of hours and the scientific approach (qualitative/quantitative and economics/mathematics). Unfortunately, creating four different lecture notes was not effective because there was a lot of overlap between them. Therefore, I decided to write a single set of lecture notes and use them for each course. This explains why some parts of this handbook are highly descriptive, but other parts are technical and require a mathematical background in probability, statistics, machine learning, linear algebra, optimization and stochastic analysis.

The publication of my previous lecture notes on risk management (Roncalli, 2020a, Handbook of Financial Risk Management) was a great disappointment. In fact, the publisher has set a high price that is prohibitive for my students. Therefore, I have decided to publish this manual for free. Whatever happens, the electronic version of this manual is and will remain free for my students and everyone else. It is available at the following web site:


Acknowledgments

I would like to thank the various people who helped me organise these academic courses, in alphabetical order: Michel Guillard, Emmanuel Gobet, Eleni Iliopulos, Claire Loupias, Gilles Pagès, Fabrice Pansard, Peter Tankov and Fabien Tripier. I would also like to thank all the Masters students who participated in my Sustainable Finance courses.

I would also like to thank all my co-authors at Amundi Asset Management, in particular Inès Barahhou, Mohamed Ben Slimane, Leila Bennani, Amina Cherief, Angelo Drei, Théo Le Guenedal, Frédéric Lepetit, Edmond Lezmi, François Lombard, Noureddine Oulid Azouz, Théo Roncalli, Raphaël Semet, Lauren Stagnol, Takaya Sekine and Jiali Xu. I have been learning about the practice of sustainable finance since I joined Amundi’s quantitative research team. The writing of these lecture notes is therefore heavily influenced by the materials and models developed at Amundi.

I would also like to thank Mohamed Ben Slimane, Théo Roncalli and Jiali Xu for reading some parts of this book and testing the exercises.

Paris, October 2023

Thierry Roncalli
<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>×</td>
<td>Arithmetic multiplication</td>
</tr>
<tr>
<td>·</td>
<td>Scalar, vector and matrix multiplication</td>
</tr>
<tr>
<td>*</td>
<td>Convolution</td>
</tr>
<tr>
<td>◦</td>
<td>Hadamard product ((x \circ y)_i = x_i y_i)</td>
</tr>
<tr>
<td>⊗</td>
<td>Kronecker product (A \otimes B)</td>
</tr>
<tr>
<td></td>
<td>(\mathcal{E})</td>
</tr>
<tr>
<td>≺</td>
<td>Preference ordering</td>
</tr>
<tr>
<td>⟨(x, x')⟩</td>
<td>Inner product of (x) and (x')</td>
</tr>
<tr>
<td>1</td>
<td>Vector of ones</td>
</tr>
<tr>
<td>(1{A})</td>
<td>The indicator function is equal to 1 if (A) is true, 0 otherwise</td>
</tr>
<tr>
<td>(1{x})</td>
<td>The characteristic function is equal to 1 if (x \in A), 0 otherwise</td>
</tr>
<tr>
<td>0</td>
<td>Zero vector</td>
</tr>
<tr>
<td>((A_{i,j}))</td>
<td>Matrix (A) with entry (A_{i,j}) in row (i) and column (j)</td>
</tr>
<tr>
<td>(A^{-1})</td>
<td>Inverse of the matrix (A)</td>
</tr>
<tr>
<td>(A^\top)</td>
<td>Transpose of the matrix (A)</td>
</tr>
<tr>
<td>(A^+)</td>
<td>Moore-Penrose pseudo-inverse of the matrix (A)</td>
</tr>
<tr>
<td>(\text{AS}(w \mid b))</td>
<td>Asset-based active share</td>
</tr>
<tr>
<td>(\text{AS}_{\text{Sector}}(w \mid b))</td>
<td>Sector-based active share</td>
</tr>
<tr>
<td>(\alpha_p)</td>
<td>Planetary albedo (default value = 0.29)</td>
</tr>
<tr>
<td>(b)</td>
<td>Vector of weights ((b_1, \ldots, b_n)) for the benchmark (b)</td>
</tr>
<tr>
<td>(\beta)</td>
<td>(\beta)-score (or Beta score)</td>
</tr>
<tr>
<td>(B(p))</td>
<td>Bernoulli distribution with parameter (p)</td>
</tr>
<tr>
<td>(B(n, p))</td>
<td>Binomial distribution with parameters (n) and (p)</td>
</tr>
<tr>
<td>(Bates(n))</td>
<td>Bates distribution with parameter (n)</td>
</tr>
<tr>
<td>(B_\lambda(\lambda, T))</td>
<td>Planck radiation law</td>
</tr>
<tr>
<td>(B(\alpha, \beta))</td>
<td>Beta distribution with parameters (\alpha) and (\beta)</td>
</tr>
<tr>
<td>(\beta_i)</td>
<td>Beta of asset (i) with respect to portfolio (w)</td>
</tr>
<tr>
<td>(\beta_i(w))</td>
<td>Another notation for the symbol (\beta_i)</td>
</tr>
<tr>
<td>(\beta(w \mid b))</td>
<td>Beta of portfolio (w) when the benchmark is (b)</td>
</tr>
<tr>
<td>(c)</td>
<td>Specific heat capacity</td>
</tr>
<tr>
<td>(\text{cov}(X))</td>
<td>Covariance of the random vector (X)</td>
</tr>
<tr>
<td>(C_i)</td>
<td>Carry of bond (i)</td>
</tr>
<tr>
<td>(C(\text{or } \rho))</td>
<td>Correlation matrix</td>
</tr>
<tr>
<td>(C_n(\rho))</td>
<td>Constant correlation matrix of size (n) with uniform correlation (\rho)</td>
</tr>
<tr>
<td>(\mathbf{CB}(t_1, t_2))</td>
<td>Carbon budget between (t_1) and (t_2)</td>
</tr>
<tr>
<td>(\text{CC})</td>
<td>Concentration rate</td>
</tr>
</tbody>
</table>
List of Symbols and Notations

\( \text{CE} \) Carbon emissions
\( \text{CI} \) Carbon intensity
\( \text{CI}^* \) Maximum carbon intensity value or threshold
\( \text{CM} \) Carbon momentum
\( \text{CM}^{\text{Long}} \) Long-term carbon momentum
\( \text{CM}^{\text{Short}} \) Short-term carbon momentum
\( \text{CPI} \) Consumer price index

\( d \) Distance
\( D \) Covariance matrix of idiosyncratic risks
\( D^\eta (p) \) Hill number (or diversity index of order \( \eta \))
\( D(a) \) Discriminant curve
\( \text{det}(A) \) Determinant of the matrix \( A \)
\( \text{diag}(a) \) Diagonal matrix with elements \( (a_1, \ldots, a_n) \)
\( \text{DTS}_i \) Duration-times-spread factor of bond \( i \)
\( \text{DTS}(w) \) Duration-times-spread factor of portfolio \( w \)
\( \delta \) Deuterium isotope ratio \( (2H/1H) \)
\( \delta^{13}C \) Carbon isotope ratio \( (13C/12C) \)
\( \delta^{18}O \) Oxygen isotope ratio \( (18O/16O) \)

\( e_i \) The value of the vector is 1 for the row \( i \) and 0 elsewhere
\( \mathbb{E}[X] \) Mathematical expectation of the random variable \( X \)
\( \mathcal{E} \) Set of edges in a graph
\( \mathcal{E}(\lambda) \) Exponential probability distribution with parameter \( \lambda \)
\( \mathcal{E} \) Energy flux (or radiation flux)
\( \mathcal{EF} \) Emission factor
\( \exp(A) \) Exponential of the matrix \( A \)
\( \varepsilon \) Emissivity

\( f(x) \) Probability density function
\( F \) Forcing
\( F_{\text{Solar}} \) Incoming solar radiation (default value = 242.82 W/m\(^2\))
\( F(x) \) Cumulative distribution function
\( F^{-1}(\alpha) \) Quantile function
\( F \) Vector of risk factors \( (F_1, \ldots, F_m) \)
\( F_j \) Risk factor \( j \)
\( F_t \) Filtration

\( g \) Greenium
\( G \) Greenness measure
\( G(p) \) Geometric distribution with parameter \( p \)
\( G = (V, E) \) Graph with vertices \( V \) and edges \( E \)
\( GI \) Green intensity
\( Gini \) Gini coefficient
\( GRS \) Green revenue share
\( \gamma \) Risk-tolerance coefficient
\( \bar{\gamma} \) Risk-aversion coefficient
\( \gamma_1 \) Skewness
\( \gamma_2 \) Excess kurtosis
\( H(p) \) Herfindahl index

\( i \) Asset (or component) \( i \)
List of Symbols and Notations

\[ I_n \] Identity matrix of dimension \( n \)
\[ I(p) \] Shannon entropy of the distribution \( p \)
\[ I(X) \] Shannon entropy of the random variable \( X \)
\[ I(X,Y) \] Shannon entropy of the random vector \( (X,Y) \)
\[ I(X \cap Y) \] Shannon entropy of the random vector \( (X,Y) \)
\[ I^*(p) \] Shannon diversity index
\[ IG(\mu,\lambda) \] Inverse Gaussian distribution with parameters \( \mu \) and \( \lambda \)
\[ IR(\omega | \beta) \] Information ratio of portfolio \( \omega \) with respect to the benchmark \( \beta \)
\[ \mathbb{K} \] State space \((1, \ldots, K)\)
\[ \kappa_{up} \] Upstreamness index of sector \( j \)
\[ \kappa_{down} \] Downstreamness index of sector \( j \)
\[ \ln(A) \] Logarithm of the matrix \( A \)
\[ \ell(\theta) \] Log-likelihood function with \( \theta \) the vector of parameters to estimate
\[ \ell_t \] Log-likelihood function for the observation \( t \)
\[ \mathcal{L}(x; \lambda) \] Lagrange function, whose Lagrange multiplier is \( \lambda \)
\[ \mathcal{L} \] Leontief inverse matrix
\[ \hat{\mathcal{L}} \] Dual inverse matrix (or upstream multiplier matrix)
\[ \mathcal{L}(p) \] Downstream multiplier matrix
\[ \lambda(p) \] Simpson index
\[ m \] \( m \)-score (or min-max score)
\[ \text{Map} \] Map function
\[ \text{MD}_i \] Modified duration of bond \( i \)
\[ \text{MD}(w) \] Modified duration of portfolio \( w \)
\[ \mu \] Vector of expected returns \((\mu_1, \ldots, \mu_n)\)
\[ \mu_i \] Expected return of asset \( i \)
\[ \mu_m \] Expected return of the market portfolio
\[ \bar{\mu} \] Empirical mean
\[ \mu(w) \] Expected return of portfolio \( w \)
\[ \mu(X) \] Mean of the random vector \( X \)
\[ \mu_m(X) \] \( m \)-th centered moment of the random vector \( X \)
\[ \mu'_m(X) \] \( m \)-th moment of the random vector \( X \)
\[ n_S \] Number of scenarios or simulations
\[ \mathcal{N}(\mu, \sigma^2) \] Normal distribution with mean \( \mu \) and standard deviation \( \sigma \)
\[ \mathcal{N}(\mu, \Sigma) \] Multivariate normal distribution with mean \( \mu \) and covariance matrix \( \Sigma \)
\[ \Omega \] Covariance matrix of risk factors
\[ p(k) \] Probability mass function of an integer-valued random variable
\[ P \] Markov transition matrix
\[ P_t \] Transition matrix at time \( t \)
\[ P(\Sigma) \] Cholesky decomposition of \( \Sigma \)
\[ \mathcal{P}(\lambda) \] Poisson distribution with parameter \( \lambda \)
\[ \mathcal{P}(x) \] Performance curve
\[ \text{PPI} \] Producer price index
\[ \pi \] Vector of risk premia
\[ \pi^* \] Stationary distribution
\[ \pi_m \] Market risk premium
\[ \pi_n^- \] 1-diversity distribution
\[ \pi_n^+ \] \( n \)-diversity distribution
\[ \phi(x) \] Probability density function of the standardized normal distribution

Handbook of Sustainable Finance
### List of Symbols and Notations

- $\phi_n(x; \Sigma)$: Probability density function of the multivariate normal distribution with covariance matrix $\Sigma$
- $\Phi(x)$: Cumulative density function of the standardized normal distribution
- $\Phi^{-1}(\alpha)$: Inverse of the cdf of the standardized normal distribution
- $\Phi_n(x; \Sigma)$: Cumulative density function of the multivariate normal distribution with covariance matrix $\Sigma$
- $q$: $q$-score (or quantile score)
- $QF(x; Q, R, c)$: Quadratic form
- $r$: Return of the risk-free asset
- $R$: Vector of asset returns ($R_1, \ldots, R_n$)
- $R_i$: Return of asset $i$
- $R_{i,t}$: Return of asset $i$ at time $t$
- $R_{m,t}$: Return of the market portfolio at time $t$
- $R(w)$: Return of portfolio $w$
- $R(t)$: Rating of the entity at time $t$
- $R(w)$: Risk measure of portfolio $w$
- $R$: Reduction rate of carbon emissions
- $R(w | b)$: Carbon footprint reduction rate of portfolio $w$ wrt benchmark $b$
- $R^2$: Coefficient of determination
- $\rho$: Correlation matrix of asset returns
- $\rho_{i,j}$: Correlation between asset returns $i$ and $j$
- $\rho(x, y)$: Correlation between portfolios $x$ and $y$
- $s$: Credit spread
- $s_j$: Mapping vector of sector $j$
- $S_{\text{sector}, j}$: Sector $j$
- $S$: ESG score
- $S^*$: Minimum ESG score or threshold
- $S_0$: Total solar irradiance at the mean Earth-Sun distance (default value = 1368 W/m$^2$)
- $S(x)$: Selection curve
- $SC_1$: Scope 1
- $SC_2$: Scope 2
- $SC_{3\text{up}}$: Upstream scope 3
- $SC_{3\text{down}}$: Downstream scope 3
- $SC_3$: Scope 3 ($= SC_{3\text{up}} + SC_{3\text{down}}$)
- $SC_{1\sim 2}$: Scope 1 and 2
- $SC_{1\sim 3}$: Scope 1, 2 and 3 ($= SC_1 + SC_2 + SC_{3\text{up}}$)
- $SC_{1\sim 3}$: Scope 1, 2 and 3
- $SR(w | r)$: Sharpe ratio of portfolio $w$ when the risk-free rate is equal to $r$
- $\sigma$: Stefan-Boltzmann constant (default value = $5.67 \times 10^{-8}$ W/m$^2$ K$^{-4}$)
- $\sigma_i$: Volatility of asset $i$
- $\sigma_m$: Volatility of the market portfolio
- $\tilde{\sigma}_i$: Idiosyncratic volatility of asset $i$
- $\hat{\sigma}$: Empirical volatility
- $\sigma(w)$: Volatility of portfolio $w$
- $\sigma(w | b)$: Tracking error volatility of portfolio $w$ wrt benchmark $b$
- $\sigma_{AS}(w | b)$: Active share active risk of portfolio $w$ wrt benchmark $b$
- $\sigma_{MD}(w | b)$: Duration active risk of portfolio $w$ wrt benchmark $b$
- $\sigma_{DTS}(w | b)$: DTS active risk of portfolio $w$ wrt benchmark $b$
- $\sigma(X)$: Standard deviation of the random variable $X$
- $\Sigma$: Covariance matrix
- $\hat{\Sigma}$: Empirical covariance matrix
List of Symbols and Notations

\( t_\nu \): Student's \( t \) distribution with \( \nu \) degrees of freedom

\( t_n (\Sigma, \nu) \): Multivariate \( t \) distribution with \( \nu \) degrees of freedom and covariance matrix \( \Sigma \)

\( \text{trace} (A) \): Trace of the matrix \( A \)

\( \mathbf{T}(x; \nu) \): Cumulative density function of the Student's \( t \) distribution with \( \nu \) degrees of freedom

\( \mathbf{T}^{-1}(\alpha; \nu) \): Inverse of the cdf of the Student's \( t \) distribution with \( \nu \) degrees of freedom

\( \mathbf{T}_n (x; \alpha, \nu) \): Cumulative density function of the \( t \) distribution with parameters \( \alpha \) and \( \nu \)

\( \mathbf{T}_2 (x_1, x_2; \rho, \nu) \): Cumulative density function of the bivariate \( t \) distribution with parameters \( \rho \) and \( \nu \)

\( \mathcal{T}(u) \): Matrix \( \mathcal{T}(u) = uu^\top \) of dimension \( n \times n \) where \( u \) is an \( n \times 1 \) vector

\( \mathcal{T} = (\mathcal{V}, \mathcal{E}) \): Tree with vertices \( \mathcal{V} \) and edges \( \mathcal{E} \)

\( \mathcal{T} \): Temperature

\( \mathcal{T}_a \): Air/atmospheric temperature

\( \mathcal{T}_e \): Effective temperature (default value = deg\( K255.81 \) or \(-17.34^\circ C\))

\( \mathcal{T}_s \): Earth's surface temperature

\( \tau \): Hitting time

\( \theta \): Vector of parameters

\( \hat{\theta} \): Estimator of \( \theta \)

\( \mathcal{U}_{[a, b]} \): Uniform distribution between \( a \) and \( b \)

\( \mathcal{U}(W) \): Utility function of the wealth \( W \)

\( \text{var}(X) \): Variance of the random variable \( X \)

\( \mathcal{V} \): Set of vertices in a graph

\( \omega \): Vector of weights \((\omega_1, \ldots, \omega_n)\) for portfolio \( \omega \)

\( \omega^\star \): Mean-variance optimized portfolio

\( \omega^\ast \): Tangency portfolio

\( \omega_i \): Weight of asset \( i \) in portfolio \( \omega \)

\( \omega_{\text{gmv}} \): Global minimum variance portfolio

\( \omega_{\text{m}} \): Market portfolio

\( W \): Wealth

\( x^+ \): Maximum value between \( x \) and 0

\( X \): Random variable

\( X_{i:n} \): \( i^{th} \) order statistic of a sample of size \( n \)

\( y \): Yield to maturity

\( z \): Altitude

\( z \): \( z \)-score (or Gaussian score)
Other scientific conventions

YYYY-MM-DD We use the international standard date notation where YYYY is the year in the usual Gregorian calendar, MM is the month of the year between 01 (January) and 12 (December), and DD is the day of the month between 01 and 31.

BP Before present (1950)

Kyr/kyr/ka 1 000 years
Myr/myr/Ma 1 000 000 years
Gyr/byr/Ga 1 000 000 000 years

USD (or $) US dollar
EUR (or €) Euro
KUSD One thousand dollars
$1 mn/bn/tn One million/billion/trillion dollars

% Percent or 0.01
‰ Per mil or 0.1%
bp Basis point or 0.01%

ppm Part per million
ppmv Part per million by volume
ppb Part per billion
ppbv Part per billion by volume

H₂O Water vapour
CO₂ Carbon dioxide
CH₄ Methane
N₂O Nitrous oxide

CO₂e Carbon dioxide equivalent

Hz Frequency (Hertz or s⁻¹)
J Energy (Joule or m² kg s⁻² or N m)
K Temperature (Kelvin)
kg Mass (kilogram)
m Length (meter)
m² Area (square meter)
m s⁻² Acceleration (meter per square second)
N Force (Newton or m kg s⁻²)
Pa Pressure (Pascal or m⁻¹ kg s⁻² or N m⁻²)
s Time (second)
W Power (Watt or m² kg s⁻³ or J s⁻¹)
Wm⁻² Irradiance (Watt per square meter or kg s⁻³)

Ton Imperial unit of weight equivalent to 1 016.047 kilograms

Tonne Metric unit of weight equivalent to 1 000 kilograms (also known as a metric ton)

gCO₂e One gram of CO₂e
kgCO₂e One kilogram of CO₂e (= 1 000 gCO₂e)
tCO₂e One tonne of CO₂e (= 1 000 kgCO₂e)
ktCO₂e One kilotonne of CO₂e (= 1 000 tCO₂e)
MtCO₂e One megatonne of CO₂e (= 10⁶ tCO₂e)
GtCO₂e One gigatonne of CO₂e (= 10⁹ tCO₂e)
gCO₂e/$ One gram of CO₂e per one dollar
tCO₂e/$ mn One tonne of CO₂e per one million of dollar
Abbreviations

ACPR Autorité de contrôle prudentiel et de résolution
AGM Annual general meeting
AI Artificial intelligence
AUM Assets under management
BAU Business as usual
BCBS Basel committee on banking supervision
BECCS Bio-energy carbon capture and storage
BIS Bank for international settlements
BMR EU benchmark regulation
BoE Bank of England

CAPM Capital asset pricing model
CAT Cap-and-trade
CBD Convention on biological diversity
CBI Climate bonds initiative
CBIRC China banking and insurance regulatory commission
CCF Corporate carbon footprint
CCS Carbon capture and storage
CDP Carbon disclosure project
CDR Carbon dioxide removal
CDSB Climate disclosure standards board
CE Carbon emissions
CEO Chief executive officer
Ceress Coalition for environmentally responsible economies
CFP Corporate financial performance
CI Carbon intensity
COP Conference of the parties
CPI Consumer price index
CRA Credit rating agency
CSDDDD Corporate sustainability due diligence directive
CSP Corporate social performance
CSR Corporate social responsibility

CSRD Corporate sustainability reporting directive
CTB Climate transition benchmark
DACCS Direct air carbon capture and storage
DDQ Due diligence questionnaire
DICE Dynamic integrated climate-economy model
DNSH Do no significant harm
DTS Duration-times-spread factor
EBA European banking authority
EC European Commission
ECB European central bank
ECS Equilibrium climate sensitivity
EDGAR Emission Database for Global Atmospheric Research
EEIO Environmentally-extended input-output model
EET European ESG template
EFDB Emission factor database
EFRAG European financial reporting advisory group
EIB European investment bank
EIOPA European insurance and occupational pensions authority
ENCORE Exploring natural capital opportunities, risks and exposure
EPICA European project for ice coring in Antarctica
ERA Extra-financial rating agency
ESAs European supervisory authorities
ESFS European system of financial supervision
ESG Environmental, social and governance
ESM European stability mechanism
ESMA European securities and markets authority
ETS Emissions trading scheme
Abbreviations

**EUGBR** EU green bonds regulation  
**Eurosif** European sustainable investment forum  
**EUTR** European Union taxonomy regulation for sustainable activities  

**FAO** Food and Agriculture Organization  
**FAs** Financial advisers  
**FDIC** Federal deposit insurance corporation  
**FIO** Federal insurance office  
**FMP** Financial market participant  
**FRB** Board of governors of the federal reserve system  
**FSB** Financial stability board  
**FSOC** Financial stability oversight council  
**FUND** Climate framework for uncertainty, negotiation, and distribution  

**GB** Green bond  
**GBP** Green bond principles  
**GC** Global Compact  
**GCM** General circulation model  
**GEVA** Greenhouse gas emissions per unit of value added  
**GFANZ** Glasgow financial alliance for net zero  
**GHG** Greenhouse gas  
**GICS** Global industry classification standard  
**GIIN** Global impact investing network  
**GISP** Greenland ice sheet project  
**GLP** Green loans principles  
**GMO** Genetically modified organism  
**GMV** Global minimum variance portfolio  
**GQE** Green quantitative easing  
**GRI** Global reporting initiative  
**GRIP** Greenland ice core project  
**GRS** Green revenue share  
**GSIA** Global sustainable investment alliance  
**GSIR** Global sustainable investment review  
**GSS** Green, social and sustainability bonds  
**GTAP** Global trade analysis project  
**GTB** Green-to-brown ratio  
**GTP** global temperature potential  
**GTS** Geologic time scale  
**GWP** Global warming potential  

**HCIS** High climate impact sector  
**HKMA** Hong Kong monetary authority  
**HLEG** High-level expert group on sustainable finance  

**IAIS** International association of insurance supervisors  
**IAM** Integrated assessment model  
**IASB** International accounting standards board  
**IBAT** Integrated Biodiversity Assessment Tool  
**ICMA** International capital market association  
**IDD** Insurance distribution directive  
**IEA** International energy agency  
**IFC** International finance corporation  
**IFRS** International financial reporting standards  
**IIFSA** International institute for applied systems analysis  
**IIIRC** International integrated reporting council  
**ILO** International labour organization  
**IMF** International monetary fund  
**IOPS** International organisation of pensions supervisors  
**IOSCO** International organization of securities commissions  
**IOT** Input-output table  
**IPCC** Intergovernmental panel on climate change  
**ISSB** International sustainability standards board  
**ITR** Implied temperature rating  
**IUCN** International union for conservation of nature  

**JSIF** Japan sustainable investment forum  
**KF** Kalman filter  
**KPI** Key performance indicator  

**LCA** Life cycle assessment  
**LP** Linear programming  
**LPI** Living planet index  
**LSEG** London Stock Exchange Group  

**MAC** Marginal abatement cost  
**MACC** Marginal abatement cost curve  
**MAS** Monetary authority of Singapore  
**MD** Modified duration  
**MiFID** Markets in financial instruments directive  
**MRIO** Multi-regional input-output model  
**MSA** Mean species abundance  
**MVO** Mean-variance optimized portfolio
Abbreviations

NACE Nomenclature statistique des activités économiques dans la Communauté Européenne
NCA National competent authority
NDC Nationally determined contribution
NFRD Non-financial reporting directive
NGFS Network of central banks and supervisors for greening the financial system
NGO Non-governmental organization
NGRIP North Greenland ice core project
NICE Nested inequalities climate-economy model
NIR National inventory report
NLP Natural langage processing
NRSRO Nationally recognized statistical rating organization
NZAM Net zero asset managers initiative
NZAOA Net zero asset owner alliance
NZBA Net zero banking alliance
NZE Net zero emissions scenario
NZFSPA Net zero financial service providers alliance
NZIA Net zero insurance alliance
NZICI Net zero investment consultants initiative
OCC Office of the comptroller of the currency
OCR Office of credit ratings
OECD Organisation for economic cooperation and development
OLR Outgoing longwave radiation
OLS Ordinary least squares
OPS One planet summit
OPSWF One planet sovereign wealth fund
ORSE Observatoire de la responsabilité sociétale des entreprises

PAB Paris aligned benchmark
PAGE Policy analysis of the greenhouse gas effect
PAI Principal adverse impact
PAII Paris aligned investment initiative
PBOC People’s Bank of China
PCAF Partnership for carbon accounting financials
PCF Product carbon footprint
PDB Pee Dee Belemnite
PPI Producer price index

PRI Principles for responsible investment
QP Quadratic programming
RCP Representative concentration pathway
RIAA Responsible investment association Australasia
RICE Regional integrated climate-economy model
RLI Red list index
RLS Recursive least squares
RTS Regulatory technical standard
SASB Sustainability accounting standards board
SB Social bond
SBP Social bond principles
SBTi Science-based targets initiative
SCC Social cost of carbon
SDA Sectoral decarbonisation approach
SDGs Sustainable development goals
SDTF Sudan divestment task force
SEC Securities and exchange commission
SF Sustainable finance
SFDR Sustainable finance disclosure reporting
SIB Social impact bond
SIF Sustainable investment forum
SLB sustainability-linked bond
SMOW Standard mean ocean water
SPO Second party opinion
SREP Supervisory review and evaluation process
SRI Socially responsible investing
SRP Supervisory review process
SSP Shared socioeconomic pathway
STAR Species Threat Abatement and Restoration metric
SWF Sovereign wealth fund
TCFD Task force on climate-related financial disclosures
TEG Technical expert group on sustainable finance
TFP Total factor productivity
TSI Total solar irradiance

UK SIF UK sustainable investment and finance association
UN United Nations
<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Full Form</th>
</tr>
</thead>
<tbody>
<tr>
<td>UN PRI</td>
<td>UN principles for responsible investment</td>
</tr>
<tr>
<td>UNECE</td>
<td>United Nations Economic Commission for Europe</td>
</tr>
<tr>
<td>UNEP</td>
<td>United Nations environment program</td>
</tr>
<tr>
<td>UNEP FI</td>
<td>United Nations environment program finance initiative</td>
</tr>
<tr>
<td>UNFCCC</td>
<td>UN framework convention on climate change</td>
</tr>
<tr>
<td>UNICEF</td>
<td>United Nations children’s fund</td>
</tr>
<tr>
<td>US SIF</td>
<td>Forum for sustainable &amp; responsible investment</td>
</tr>
<tr>
<td>VBDO</td>
<td>Vereniging van beleggers voor duurzame ontwikkeling</td>
</tr>
<tr>
<td>WACI</td>
<td>Weighted average carbon intensity</td>
</tr>
<tr>
<td>WAIS</td>
<td>West Antarctic ice sheet project</td>
</tr>
<tr>
<td>WBCSD</td>
<td>World business council for sustainable development</td>
</tr>
<tr>
<td>WCW</td>
<td>Who cares wins</td>
</tr>
<tr>
<td>WDPA</td>
<td>World Database on Protected Areas</td>
</tr>
<tr>
<td>WHO</td>
<td>World health organization</td>
</tr>
<tr>
<td>WIOD</td>
<td>World input-output database</td>
</tr>
<tr>
<td>WMO</td>
<td>World meteorological organization</td>
</tr>
<tr>
<td>WRI</td>
<td>World resources institute</td>
</tr>
</tbody>
</table>
Chapter 1

Introduction

In this chapter, we first define the concept of sustainable finance (SF) and discuss its historical origins, especially the motivations of responsible investors. We also present the ecosystem of responsible investing and the corresponding regulatory framework. Finally, we give some figures about the market of sustainable finance.

1.1 Definition

The European Commission defines the concept of sustainable finance as follows\(^1\):

“Sustainable finance refers to the process of taking environmental, social and governance (ESG) considerations into account when making investment decisions in the financial sector, leading to more long-term investments in sustainable economic activities and projects. Environmental considerations might include climate change mitigation and adaptation, as well as the environment more broadly, for instance the preservation of biodiversity, pollution prevention and the circular economy. Social considerations could refer to issues of inequality, inclusiveness, labour relations, investment in human capital and communities, as well as human rights issues. The governance of public and private institutions — including management structures, employee relations and executive remuneration — plays a fundamental role in ensuring the inclusion of social and environmental considerations in the decision-making process.”

In this definition, the EC also introduces the concept of ESG (Environmental, Social and Governance), which is very popular among asset owners and managers. For instance, in contrast to business as usual (BAU) or traditional investing, the goal of ESG investing is to take into account extra-financial analysis when performing asset selection. Nevertheless, the frontier between SF and ESG is not very clear. This is also the case with other terms that are frequently used such as responsible investment (RI), sustainable investing (SI) and socially responsible investing (SRI). We report here some definitions we can find in financial textbooks:

- **Responsible investment** is an approach to investment that explicitly acknowledges the relevance to the investor of environmental, social and governance factors, and of the long-term health of the market as a whole.

- **Sustainable investing** is an investment approach that considers environmental, social and governance factors in portfolio selection.

- **Socially responsible investing** is an investment strategy that is considered socially responsible, because it invests in companies that have ethical practices.

- **ESG** refers to the factors that measure the sustainability of an investment.

In fact, it is really difficult to make the difference between all these concepts, because they both encompass the same underlying idea. Therefore, we can consider them as the same subject (Figure 1.1). We can complete this list by other expressions such as green finance, climate finance, blue finance, etc. Generally, the term green finance is reserved for the environmental pillar, whereas blue finance is an emerging area in climate finance and concerns the ocean economy (IFC, 2022).

Figure 1.1: Many words, one concept

1.2 **Short history of responsible and ethical investing**

From an historical point of view, we observe three stages. In the 1990s and 2000s, the word “sustainable finance” is not really used. The term “responsible investment” is preferred because of the ethical considerations of some final investors and asset owners. In the 2010s, “ESG investing” takes the lead because it gains momentum in the asset management industry. Moreover, ESG rating agencies adopted the break down of the extra-financial information into environmental, social and governance pillars. Finally, the concept of ESG spreads across all financial actors and sectors (e.g., corporates, banks, regulators, policy makers and central banks). In this context, the investment side is not only concerned, but it also affects financing, regulation, society and public policies. Therefore, it is better to use the term “sustainable finance”, which is more generic than responsible or ESG investing.

The previous evolution (responsible investment → ESG → sustainable finance) can be explained by the history of ethical investment. Religious motivations explained the first examples of responsible (or faith-based) investing. In 1758, the Quaker Philadelphia yearly meeting prohibited members from participating in the slave trade (buying or selling humans). They are followed by religious groups (e.g., Muslims, or Methodists), which invited people and members to avoid investing in companies linked to weapons, tobacco, alcohol, or gambling. According to Beabout and Schmiesing (2003), the first SRI mutual fund (Pioneer Fund) was created in 1928 by Philip Carret for Evangelical
Protestants. The years 1930-1960 saw the emergence of several doctrines about responsible investing. In particular, a number of corporate scandals lead to more focus on governance issues. During the Vietnam War, shareholders organized resolutions against the production of napalm\textsuperscript{2} and Agent Orange\textsuperscript{3}. Therefore, we observe the development of engagement policies besides exclusion policies. In 1971, two members of the United Methodist Church (Luther Tyson and Jack Corbett) and the portfolio manager Tony Brown launched the Pax World fund, which may also claim to be the first sustainable mutual fund in the United States. Indeed, the strategy of the fund mixed both financial and social criteria. This is a step forward since the fund considers selection screening and not only exclusion screening. Moskowitz (1972) published a first list of socially responsible stocks, including Chase Manhattan, Johnson Products, Levi Strauss, New York Times, Whirlpool and Xerox. These stocks are challenged by Vance (1975), who found that they have largely underperformed the Dow Jones from 1972 to 1975. The concept of “\textit{sin stocks}” was born, and the relationship between responsible investment and profitability led to many academic publications on these topics. This first period of sustainable finance may be summarized as follows:

\textit{“Do no harm. That is the central concept of traditional faith-based investing and, to some degree, the central concept of socially responsible investing: Avoiding products or industries that conflict with a set of moral values.”} (Townsend, 2020, page 2).

The question of moral values is also the main factor explaining the development of corporate social responsibility (CSR). This theory begins with the publication of “\textit{Social Responsibilities of the Businessman}” by Bowen (1953). In this book, the author analyzed the responsibilities to society that companies are expected to assume. Considered as the “\textit{Father of Corporate Social Responsibility}” (Carroll, 1999), Howard Bowen assumed that “\textit{CSR can help business reach the goals of social justice and economic prosperity by creating welfare for a broad range of social groups, beyond the corporations and their shareholders}.” Regarded as an alternative to socialism and pure capitalism, CSR is rejected by neoclassical economists. One of the most famous opponents is Milton Friedman:

\textit{“There is one and only one social responsibility of business — to use its resources and engage in activities designed to increase its profits so long as it stays within the rules of the game, which is to say, engages in open and free competition without deception or fraud.”} (Friedman, 1962).

In particular, his article published in New York Times (Friedman, 1970) has a big impact on the shareholder vs. stakeholder debate. The stakeholder theory suggests that the real success of a company lies in satisfying all its stakeholders, not just the shareholders (Freeman, 2004). The stakeholder ecosystem involves customers, suppliers, employees, local communities, governmental agencies, financiers, and others. In this theory, each business entity creates, and sometimes destroys, value for each stakeholder group. Again, many academic research have been published on this topic, in particular how to define corporate social performance (CSP), and its relationship with corporate financial performance (CFP). Nevertheless, even if the debate is still raging, the stakeholder theory has profoundly changed the vision for the business. Indeed, there’s today a wide consensus that business objective should not just be about profit maximization. An example is the Global Compact (GC) initiative created by the UN Secretary-General Kofi Annan on July 2000. It is a voluntary

\textsuperscript{2}In 1968, the Medical Committee for Human Rights acquired shares in Dow Chemical in order to prohibit sales of napalm.

\textsuperscript{3}Agent Orange is a mixture of two herbicides. It was used by the US military to defoliate forests and terrorize populations in South Vietnam (Townsend, 2020, page 3).
initiative based on CEO commitments to implement a set of human rights, labour, environmental, and anti-corruption principles\textsuperscript{4}. The 10 principles are:

- **Human rights**

  1. Businesses should support and respect the protection of internationally proclaimed human rights; and
  2. Make sure that they are not complicit in human rights abuses.

- **Labour**

  3. Businesses should uphold the freedom of association and the effective recognition of the right to collective bargaining;
  4. The elimination of all forms of forced and compulsory labour;
  5. The effective abolition of child labour; and
  6. The elimination of discrimination in respect of employment and occupation.

- **Environment**

  7. Businesses should support a precautionary approach to environmental challenges;
  8. Undertake initiatives to promote greater environmental responsibility; and

- **Anti-corruption**

  10. Businesses should work against corruption in all its forms, including extortion and bribery.

From 2004 to 2008, the UN Global Compact, the International Finance Corporation (IFC) and the Swiss government sponsored a series of annual conferences for investment professionals, asset managers, and financial institutions to develop guidelines and recommendations on how to better integrate environmental, social and corporate governance issues. The term ESG was first coined in the 2004 conference report “Who Cares Wins — Connecting Financial Markets to a Changing World” (WCW, 2004) and was popularized by the next four reports\textsuperscript{5}.

Socially responsible investing does not only concern corporations, but also sovereigns and countries. For instance, the US Congress passed in 1986 the “Comprehensive Anti-Apartheid Act”, banning new investment in South Africa. Similarly, the Sudan Divestment Task Force (SDTF) was formed in 2005 to coordinate and provide resources for the Sudan divestment campaign in response to the genocide occurring in the Darfur region. The US “Sudan Accountability and Divestment Act” came into force in December 2007. It authorized a state or local governments to divest assets in companies that are conducting business operations in Sudan that include power production activities, mineral extraction activities, oil-related activities, or the production of military equipment.

\textsuperscript{4}The Global compact initiative takes its root in the code of conduct for companies developed in 1977 by Leon Sullivan, a clergyman and civil rights leader. The original Sullivan Principles consisted of seven requirements a corporation operating in South Africa must satisfy. They were a response to apartheid and an alternative to complete divestment, which was perceived as a costly strategy (Grossman and Sharpe, 1986; Rudd, 1979).

According to Townsend (2020), the current concept of sustainable finance mixes “the traditional North American model for socially responsible investing, and ESG, which first took hold in Europe”. It is true that the Who Cares Wins (WCW) conferences had rather a European orientation, with participants mainly coming from European asset owners and managers, especially the 2005 conference (WCW, 2005). While SRI is more an exclusion and qualitative process at its inception in North America, ESG is a best-in-class and quantitative process when it is implemented at the beginning of the 2000s. The growth of ESG data and ESG rating agencies largely explains this shift. One reason is “the strong intellectual and legal debate on the relationship between fiduciary duty and issues of sustainability” (Townsend, 2020, page 6). In 2005, UNEP invited the law firm Freshfields Bruckhaus Deringer to produce a report about the legal use to integrate ESG issues by pension funds, insurance companies and asset managers. The objective of the report was to answer the following question:

“Is the integration of environmental, social and governance issues into investment policy (including asset allocation, portfolio construction and stock-picking or bond-picking) voluntarily permitted, legally required or hampered by law and regulation; primarily as regards public and private pension funds, secondarily as regards insurance company reserves and mutual funds?” (Freshfields Bruckhaus Deringer, 2005, page 6).

The 154-pages report analyzed the legal framework for institutions in Australia, Canada, France, Germany, Italy, Japan, Spain, the UK and the US. While the analysis is very technical and the results depends on the jurisdiction, the report concluded that integrating ESG issues is consistent with fiduciary duty if ESG factors impact the investment value and long-term risks. In this context, we observe an increasing change of European institutional investors, who consider that their fiduciary duties require them to incorporate ESG into investment analysis. As institutional investors are sophisticated investors and they base their decisions on an in-depth quantitative analysis, this has implied to transform the original qualitative approach based on discretionary exclusions to a more systematic model based on extra-financial quantitative data.

A second reason that explains the shift from a qualitative-oriented SRI to a quantitative-oriented ESG is the climate change factor. In response to global warming, the Intergovernmental Panel on Climate Change (IPCC) was established in 1988 by the World Meteorological Organization (WMO) and United Nations Environment Programme (UNEP). The IPCC prepares assessment reports about knowledge on climate change. The first assessment report (AR1) was published in March 1990, whereas the synthesis of the last assessment report (AR6) is expected in December 2022. These reports are extensively used in the United Nations Climate Change conferences. In June 1992, the Earth Summit held in Rio de Janeiro produced two important legal agreements: the Convention on Biological Diversity (CBD) and the UN Framework Convention on Climate Change (UNFCCC). The objective of this international treaty is to reduce environmental impacts across the globe. The implementation of the UNFCCC to address global warming is an on-going process. For instance, the Kyoto Protocol negotiated in 1997 and the Paris Agreement adopted in 2015 are certainly the two famous international treaties on climate change. On the investor side, the Coalition for environmentally responsible economies (Ceres) was founded in 1989 with the aim of changing corporate environmental practices. Following the Exxon Valdez oil spill, Ceres created the Valdez Principles. In 2000, it also launched the Global Reporting Initiative (GRI) to standardize corporate disclosure on ESG issues.

---

6This topic will be elaborated in the next chapter.

7The 10 principles are (1) protection of the biosphere, (2) sustainable use of natural resources, (3) reduction and disposal of wastes, (4) energy conservation, (5) risk reduction, (6) safe products and services, (7) environmental restoration, (8) informing the public, (9) management commitment, and (10) audits and reports.
The last twenty years have strengthened the place of ESG in finance, not only on the investment side, but also on the financing side. Regulators are now involved, accounting standards have been developed, climate change is recognized as a key risk factor, controversies may harm corporate reputation, social pressure impacts corporate governance, etc. In the next chapters, we will extensively document the evolution of sustainable finance during the last period. The motivations to implement a socially responsible investment are now multiple. In Figure 1.2, we give some reasons. They can be classified into two groups. The first one (economic sustainability, moral values and social pressure) is related to the "do not harm principle", and can be applied to many situations or decisions. The second group, which includes financial performance, fiduciary duty and risk management, is related to investment principles. The underlying idea is that ESG risks have to be managed and can not be ignored within portfolio construction.

Figure 1.2: The raison d'être of sustainable finance

1.3 The ESG ecosystem

As we have just seen, the ESG landscape involves many financial actors. First, investors are in the center of the ecosystem. Generally, we distinguish asset owners and managers. Asset owners correspond to end-investors and include pension funds, institutional investors, sovereign wealth funds (SWF), insurance companies, endowments and foundations, family offices, retail investors, etc. On the contrary, the asset management industry manages funds for end-investors. In this category, we have mutual funds, hedge funds, private equity funds, infrastructure funds, third-party distributors, etc. We could also mention ESG index providers since they are essential for passive management. Asset managers act then as financial intermediary between the financial markets (e.g., equity and fixed-income markets) and the saving of households, companies and organizations. While asset owners and managers constitutes the investing side, banks and issuers form the financing side. Therefore, sustainable finance also concerns the emission of debt and the structuring of ESG products such as green bonds.
1.3.1 Sustainable investment forum

The sustainable investment forums (SIF) are membership-based sustainable and responsible investment organisations. They work to promote a broader adoption of sustainable and responsible investment practices and more generally for a broader adoption of sustainability matters into financial markets and the investment chain. They are organized by countries or regions. For instance, the European Sustainable Investment Forum (Eurosif) was launched in 2001 and groups together Forum per la Finanza Sostenibile (Italy), Forum Nachhaltige Geldanlagen (Germany), Forum pour l’Investissement Responsable (France), Foro de Inversión Sostenible (Spain), Sustainable Finance Ireland, Swiss Sustainable Finance (Switzerland) and UK Sustainable Investment and Finance Association. Other SIFs are the Responsible Investment Association Australasia\(^8\) (RIAA), the Responsible Investment Association Canada (RIA Canada), The Forum for Sustainable & Responsible Investment (US SIF), the Dutch Association of Investors for Sustainable Development\(^9\) (VBDO) and the Japan Sustainable Investment Forum (JSIF). All these organizations are members of the Global Sustainable Investment Alliance (GSIA).

These forums have been created at different dates, reflecting the evolution of sustainable finance. For example, US SIF was founded in 1984 and is the oldest SIF. It is followed by RIA Canada in 1990, UK SIF in 1991 and VBDO in 1995. Most of European forums were established in 2001 (e.g., Germany, France, Italy). The main activities of these sustainable investment forums are public policy, education, training, research and promoting sustainable investing best practices. Founded in 2010, GSIA is in charge of aggregating responsible investment market data from its members in order to analyze the global sustainable investment market and the evolution of ESG trends. In particular, it publishes a biennial Global Sustainable Investment Review or GSIR (GSIA, 2013, 2015, 2017, 2019, 2021). The 2022 GSIR edition is expected mi-year 2023. We will extensively used these reports in Section 1.5 on page 38 when we will analyse the market of ESG investing.

Figure 1.3: 2018 & 2020 GSIA reports

1.3.2 Initiatives

In this section, we present the most relevant initiatives (PRI, Climate action 100+ and net zero alliances). We also list other initiatives that participate in the ESG ecosystem. Some of them will be detailed further in the next chapters.

---

\(^8\)It groups together Australia and New Zealand.

\(^9\)The Dutch name is Vereniging van Beleggers voor Duurzame Ontwikkeling.

Handbook of Sustainable Finance
Principles for responsible investment

In early 2005, the UN Secretary-General Kofi Annan invited a group of the world’s largest institutional investors to join a process to develop the Principles for Responsible Investment (PRI). A 20-person investor group drawn from institutions in 12 countries was supported by a 70-person group of experts from the investment industry, intergovernmental organisations and civil society. The PRI were launched in April 2006 at the New York Stock Exchange.

Box 1.1: PRI signatories’ commitment

“As institutional investors, we have a duty to act in the best long-term interests of our beneficiaries. In this fiduciary role, we believe that environmental, social, and corporate governance (ESG) issues can affect the performance of investment portfolios (to varying degrees across companies, sectors, regions, asset classes and through time).

We also recognise that applying these Principles may better align investors with broader objectives of society. Therefore, where consistent with our fiduciary responsibilities, we commit to the following:

- Principle 1: We will incorporate ESG issues into investment analysis and decision-making processes.
- Principle 2: We will be active owners and incorporate ESG issues into our ownership policies and practices.
- Principle 3: We will seek appropriate disclosure on ESG issues by the entities in which we invest.
- Principle 4: We will promote acceptance and implementation of the Principles within the investment industry.
- Principle 5: We will work together to enhance our effectiveness in implementing the Principles.
- Principle 6: We will each report on our activities and progress towards implementing the Principles.

The Principles for Responsible Investment were developed by an international group of institutional investors reflecting the increasing relevance of environmental, social and corporate governance issues to investment practices. The process was convened by the United Nations Secretary-General.

In signing the Principles, we as investors publicly commit to adopt and implement them, where consistent with our fiduciary responsibilities. We also commit to evaluate the effectiveness and improve the content of the Principles over time. We believe this will improve our ability to meet commitments to beneficiaries as well as better align our investment activities with the broader interests of society.

We encourage other investors to adopt the Principles.”

Source: https://www.unpri.org.

10 UN PRI and PRI are two interchangeable terms. For example, the website url is https://www.unpri.org. Nevertheless, PRI is the official term.
Signatories’ commitment is reported in Box 1.1. The principles are voluntary and aspirational, and offer a set of possible actions for incorporating ESG issues into investment practice. For instance, here are some possible actions for Principle 1:

- Address ESG issues in investment policy statements;
- Support development of ESG-related tools, metrics, and analyses;
- Advocate ESG training for investment professionals;
- Etc.

Becoming a signatory requires to pay an annual fee\(^\text{11}\), but there are no other formal requirements when the membership agreement is signed. Nevertheless, signatories are required to report on their responsible investment activities annually. The answers of the members, which form the transparency report, are public and available to anyone\(^\text{12}\). Since 2019, members must also fill in a climate transparency report, which contains specific indicators regarding the management of risks and opportunities related to climate change. These indicators are modelled on the disclosure framework of the Task Force on Climate-related Disclosures (TCFD). Based on the transparency report, PRI produces an assessment report for each member, which consists of a series of scores on several dimensions (from 0 to 100) and a rating system (from one to five stars). The assessment report is confidential, except if the member choose to make it public. It is also used by PRI to verify that signatories meet minimum requirements. If it is not the case, PRI engage with the member (one-on-one sessions, action plans, etc.). Delisting is a last resort if a signatory has not met the requirements after the two-year period. Since 2018, 165 signatories have been identified as not meeting the minimum requirements. PRI has delisted 5 signatories, and 23 other members of the 165 identified have been delisted on a voluntarily basis.

In Figure 1.4, we show the PRI growth. At the inception date, most of the 63 founding signatories were asset owners\(^\text{13}\) with a few asset managers\(^\text{14}\) and data providers\(^\text{15}\). They were mainly located in the US, Canada, UK, France\(^\text{16}\), the Netherlands and the Nordics. As of September 2022, the PRI has 5 020 signatories, representing approximately $121 trillion of assets under management (AUM). Investment managers is the most represented category (76%) followed by asset owners (14%) and service providers (10%). We observe a rapid evolution since 2015, and even an acceleration since 2021, especially in Asia and emerging markets.

**Climate action 100+**

Climate Action 100+ is an investor initiative to ensure the world’s largest corporate greenhouse gas emitters take necessary action on climate change. It was formed in the wake of the 2015

---

11The 2022/23 fee goes from £478 to £14,222 depending of the size and the category (asset owners, investment managers and service providers) of the signatory.

12The reports from 2014 to 2020 are available at the webpage [https://www.unpri.org/signatories/reporting-and-assessment/public-signatory-reports](https://www.unpri.org/signatories/reporting-and-assessment/public-signatory-reports), whereas the more recent reports can be downloaded in the data portal (or PRI’s central depository for signatories’ reporting data): [https://ctp.unpri.org/dataportalv2](https://ctp.unpri.org/dataportalv2).

13The most important were AP2, BT Pension Scheme, CDC, CDPQ, CalPERS, CPPIB, ERAFP, FRR, NYCERS, NZSF, NGPF, PGGM, TIAA-CREF, UNJSPF and USS.

14The best known asset managers were ABN AMRO Asset Management, Aviva Investors, BNP PAM, Candriam, CAAM (now Amundi), Daiwa AM, Henderson Global Investors and Threadneedle AM.

15e.g., Ethix, Trucost and Vigeo.

16There are 8 founding signatories: BNP PAM, CDC, CAAM (now Amundi), ERAFP, FRR, Groupama AM, Macif Gestion and Vigeo.
Climate Action 100+, and is launched in December 2017. It is supported by 700 investors, responsible for over $68 trillion in assets under management. Climate Action 100+ focuses on engagement, and coordinates the efforts of the investor signatories. In a nutshell, engagement corresponds to the active dialogue between the investor and the company by discussing sustainability risks and providing the investor’s expectations of corporate behavior. The main objectives are improving the climate performance of the company, reducing GHG emissions across the value chain and ensuring transparent disclosure. The engagement process van de described as follows:

- Engagement with focus company executives and board members is spearheaded by a lead investor or investors, who work cooperatively with a number of collaborating investors and are supported by technical experts.

- When signing on to the initiative, investors are asked to nominate which focus companies they wish to engage with and whether this is as a lead investor or collaborating investor.

- Engagement takes several forms, e.g., holding meetings with companies, making a statement at a company AGM, supporting shareholder resolutions on climate change, voting for the removal of directors who have failed in their accountability of climate change risks.

Climate Action 100+ engagement focuses on 166 companies, accounting for up to 80% of global corporate industrial greenhouse gas emissions. The geographic breakdown is the following: 1.8% in Africa, 20.4% in Asia, 9.0% in Australasia, 33.5% in Europe, 32.3% in North America, and 3.0% in South America. The sector distribution is reported in Table 1.1, where we indicate the number of companies and the market capitalization.\footnote{The market capitalization is computed as of 15 December 2020.} For example, the 5 focus companies for the airlines...
sector are Air France, American Airlines, Delta Air Lines, Qantas Airways, United Airlines, the 12 focus companies for the automobiles sector are BMW, Ford, General Motors, Honda, Mercedez-Benz, Nissan, Renault, SAIC, Stellantis, Suzuki, Toyota, Volkswagen, etc.

Table 1.1: Sector breakdown of Climate Action 100+ engagement

<table>
<thead>
<tr>
<th>Sector</th>
<th>Frequency</th>
<th>Market capitalisation</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Number</td>
<td>in %</td>
</tr>
<tr>
<td>Airlines</td>
<td>5</td>
<td>3.0%</td>
</tr>
<tr>
<td>Automobiles</td>
<td>12</td>
<td>7.2%</td>
</tr>
<tr>
<td>Cement</td>
<td>11</td>
<td>6.6%</td>
</tr>
<tr>
<td>Chemicals</td>
<td>7</td>
<td>4.2%</td>
</tr>
<tr>
<td>Coal mining</td>
<td>4</td>
<td>2.4%</td>
</tr>
<tr>
<td>Consumer goods &amp; services</td>
<td>12</td>
<td>7.2%</td>
</tr>
<tr>
<td>Diversified mining</td>
<td>10</td>
<td>6.0%</td>
</tr>
<tr>
<td>Electric utilities</td>
<td>30</td>
<td>18.1%</td>
</tr>
<tr>
<td>Oil &amp; gas</td>
<td>39</td>
<td>23.5%</td>
</tr>
<tr>
<td>Oil &amp; gas distribution</td>
<td>5</td>
<td>3.0%</td>
</tr>
<tr>
<td>Other industrials</td>
<td>13</td>
<td>7.8%</td>
</tr>
<tr>
<td>Other transportation</td>
<td>7</td>
<td>4.2%</td>
</tr>
<tr>
<td>Paper</td>
<td>2</td>
<td>1.2%</td>
</tr>
<tr>
<td>Shipping</td>
<td>1</td>
<td>0.6%</td>
</tr>
<tr>
<td>Steel</td>
<td>8</td>
<td>4.8%</td>
</tr>
<tr>
<td>Total</td>
<td>166</td>
<td>100.0%</td>
</tr>
</tbody>
</table>

Source: [https://www.climateaction100.org/whos-involved/companies](https://www.climateaction100.org/whos-involved/companies).

**Net zero alliances**

Net zero emissions refers to a state in which the greenhouse gases going into the atmosphere are balanced by removal out of the atmosphere. This is a condition to stop global warming. According to IPCC (2018), global temperature increase needs to be limited to 1.5°C pre-industrial levels in order to mitigate the worst impacts of climate change and preserve a livable planet. Generally, we assume that net zero emissions must be achieved by 2050 IEA (2021), otherwise multiple tipping points could be triggered with irreversible impacts.

The concept of “Net Zero Alliance” starts with the launch of the Net Zero Asset Owner Alliance (NZAOA) in September 2019 under the umbrella of UNEP FI. In September 2022, the Alliance counts 74 members, accounting for $10.6 tn in AUM (UNEP, 2022). These members must satisfy a common protocol to target setting and reporting based on four components:

1. Engagement targets
   - Engage with 20 companies focusing on those with highest owned emissions or those responsible for combined 65% owned emissions in portfolio.

2. Sub-portfolio emission targets
   - 22 to 32% CO₂e reduction by 2025 (per IPCC 1.5°C SR scenarios);
   - 49 to 65% CO₂e reduction by 2030 (per IPCC 1.5°C SR scenarios);
• Cover portfolio scope 1 + 2 emissions, tracking of scope 3, and use absolute or intensity-based reduction KPIs.

3. Sector targets

• Use absolute or intensity-based reductions on all material sectors;
• Scope 3 to be included wherever possible;
• Sector specific intensity KPIs recommended.

4. Financing transition targets

• Reporting progress on a climate-positive trend for all Alliance members internally to the Alliance;
• Build solutions or enhance climate solution reporting.

For example, the targets defined by Munich Re are the following: (1) concentrate on and engage with large contributors of financed emissions within the listed equities and corporate bond portfolio; (2) reduce the absolute emissions of listed equities, corporate bond and real estate portfolio by \(25 - 29\%\) (scope 1 + 2 emissions of investee companies) by 2025; (3) reduce emissions for listed equities and corporate bonds for thermal coal \((-35\%)\) and oil & gas \((-25\%\)) ; (4) double the renewable portfolio (equity and debt) from €1.6 bn to €3 bn.

In June 2020, UNFCCC launches the “Race to Zero” campaign, which have definitively accelerated the net zero commitments. For example, the Glasgow Financial Alliance for Net Zero (GFANZ) is created in April 2021 by Mark Carney\(^{19}\) and the COP26 presidency to coordinate efforts across all sectors of the financial system to accelerate the transition to a net zero global economy\(^{20}\). GFANZ is an umbrella organisation covering seven net zero initiatives: NZAOA, the Net Zero Asset Managers initiative (NZAM), the Paris Aligned Investment Initiative (PAII), the Net Zero Banking Alliance (NZBA), the Net Zero Insurance Alliance (NZIA), Net Zero Financial Service Providers Alliance (NZFSPA) and the Net Zero Investment Consultants Initiative (NZICI).

Other initiatives

There are a growing list of initiatives that are related to ESG issues. Here are a few examples with respect to the three pillars:

• Environmental
  Asia Investor Group On Climate Change (AIGCC), Finance for Biodiversity Pledge, Finance for Tomorrow, Institutional Investors Group on Climate Change (IIGCC), Montreal Carbon Pledge, One Planet Sovereign Wealth Fund (OPSWF), Portfolio Decarbonization Coalition, etc.

---

\(^{18}\) The reader can consult the web page https://www.unepfi.org/net-zero-alliance/resources/member-targets to retrieve the 2025 member targets.

\(^{19}\) Mark Carney was the governor of the Bank of Canada from 2008 to 2013, the governor of the Bank of England from 2013 to 2020 and the chairman of the Financial Stability Board from 2011 to 2018. Since 2020, he is a United Nations special envoy for climate action and finance.

\(^{20}\) We report here the press release of November 3, 2021 during the COP 26 summit: “Today, through the Glasgow Financial Alliance for Net Zero (GFANZ), over $130 trillion of private capital is committed to transforming the economy for net zero. These commitments, from over 450 firms across 45 countries, can deliver the estimated $100 trillion of finance needed for net zero over the next three decades.”
• Social
  Platform Living Wage Financials (PLWF), PRI Human Rights Engagement, Tobacco-Free Finance Pledge, Workforce Disclosure Initiative (WDI), etc.

• Governance
  Australian Shareholders’ Association (ASA), European Corporate Governance Institute (ECGI), International Corporate Governance Network (ICGN), Say on Climate, etc.

1.3.3 Regulators

While regulators and supervisors were absent from the ESG ecosystem for a long time, they are now at the forefront of the ESG debate. The main reason is the phenomenal growth of ESG and climate investing, and the change of motivations. As long as responsible investing was driven by moral values, ESG investing concerned a small market of investors. Today, ESG has become a marketing argument and the risk of ESG-washing and greenwashing has become very high. We must distinguish two types of risk:

• Explicit & deliberate greenwashing;

• Unintentional greenwashing.

Deliberate greenwashing is a mis-selling risk, which is a subject of close scrutiny from supervisors. An example is the DWS scandal\(^\text{21}\). Unintentional greenwashing is a misinterpretation risk, which must be clarified by regulators\(^\text{22}\). An example is the definition of a net zero investment policy. In this context, clients must be protected from both types of greenwashing risk. Another reason that explains the recent interest of regulators is the political will to mitigate global warming. Indeed, financial regulation is certainly one of the most important instruments to achieve this goal. Therefore, it is no coincidence if the financial sector is expected to play a key role in helping to decarbonize the corporate sector.

Table 1.2: The supervision institutions in finance

<table>
<thead>
<tr>
<th>Banks</th>
<th>Insurers</th>
<th>Markets</th>
<th>All sectors</th>
</tr>
</thead>
<tbody>
<tr>
<td>Global</td>
<td>BCBS</td>
<td>IAIS</td>
<td>IOSCO</td>
</tr>
<tr>
<td>EU</td>
<td>EBA/ECB</td>
<td>EIOPA</td>
<td>ESMA</td>
</tr>
<tr>
<td>US</td>
<td>FDIC/FRB</td>
<td>FIO</td>
<td>SEC</td>
</tr>
</tbody>
</table>

Regulators in charge of sustainable risk are the same than those in charge of traditional risks (e.g., market risk, credit risk or liquidity risk). In Table 1.2, we have reported a list of supervision institutions in finance. At the global level, four international authorities have primary responsibility of the financial regulation: the Basel Committee on Banking Supervision (BCBS), the International Association of Insurance Supervisors (IAIS), the International Organization of Securities Commissions (IOSCO) and the Financial Stability Board (FSB). The FSB, which is in charge of the systemic risk regulation, has identified climate risk at a very early stage. The speech “Breaking the tragedy

\(^{21}\)See the Financial Times’ article on litigation issues of ESG investing: [https://www.ft.com/content/1094d5da-70bf-40b5-98f4-725d50620a5a](https://www.ft.com/content/1094d5da-70bf-40b5-98f4-725d50620a5a).

\(^{22}\)Here, we make the difference between regulation and supervision from a risk management viewpoint (Roncalli, 2020a, page 12). The regulator is responsible of setting rules and policy guidelines. The supervisor evaluates the safety and soundness of financial institutions and verifies that the regulation rules are applied. For example, in Europe, the regulator of the banking sector is EBA while the supervisor is ECB.
of the horizon” by Mark Carney, Chairman of the FSB, at London, 29 September 2015, marked a turning-point in the recognition of climate change as a big risk for the financial stability (Carney, 2015). According to Mark Carney, the financial stability can be affected through three channels: physical risk (the impact on insurance liabilities and financial assets that arise today from climate extreme events), liability risk (the impacts that could arise tomorrow if parties who have suffered from climate change seek compensation from those they hold responsible) and transition risk (the financial risk that could result from the process of adjustment towards a lower-carbon economy). Following the G20 Antalya Summit, the FSB proposed then to “establish an industry-led disclosure task force, to design and deliver voluntary standards for effective disclosures that meet the needs of investors and creditors” (FSB, 2015). The Task Force on Climate-related Financial Disclosures (TCFD) is created in December 2015 under the chairmanship of Michael Bloomberg. In June 2017, TCFD released its final climate-related financial disclosure recommendations. The first status report on disclosure practices is published in September 2018. Disclosures is the first pillar of the FSB roadmap, which covers three other areas: (1) data, (2) vulnerability analysis and (3) regulatory and supervisory practices and tools (Figure 1.5).

The Basel Committee on Banking Supervision (BCBS) provides a forum for regular cooperation on banking supervisory matters. Its main objective is to improve the quality of banking supervision worldwide. Its first publication on climate-related financial risks dates back to April 2020. In June 2022, BCBS released its first guidelines on this topic (BCBS, 2022). These guidelines includes 12 principles for the effective risk management of climate risk and 6 principles for the supervisory review process (SRP). We report here the first principle, which states that climate risk must be managed such as financial risks (e.g., market risk or credit risk):

“Banks should develop and implement a sound process for understanding and assessing the potential impacts of climate-related risk drivers on their businesses and on the envi-
Chapter 1. Introduction

Ronments in which they operate. Banks should consider material climate-related financial risks that could materialise over various time horizons and incorporate these risks into their overall business strategies and risk management frameworks.” (BCBS, 2022, page 2).

Since we know that BCBS is able to rapidly develop new regulatory frameworks, we can expect the publication of new standards including climate risk in the coming years. Concerning the two other global supervision institutions, IOSCO has produced a report on ESG rating agencies and data providers (IOSCO, 2021) whereas IAIS is more focusing on climate risk and its supervision in the insurance sector (IAIS, 2021). It is interesting to notice that supervisors of the asset management industry are more focused on ESG data while supervisors of the insurance industry are more concerned by the physical risk.

We also observe a rapid transformation of the regulatory framework at the regional or national level. For instance, a new SEC rule requires all registrants to disclose information on climate risks23. The sustainable finance roadmap 2022-2024 identifies three priorities for ESMA24: (1) tackling greenwashing and promoting transparency, (2) building NCAs’ and ESMA’s capacities and (3) monitoring, assessing and analysing ESG markets and risks. The banking supervision has already conducted several climate stress testing programs (ACPR, 2021; Bank of England, 2022; ECB, 2022). Central banks are also very active. Thus, the Network of Central Banks and Supervisors for Greening the Financial System (NGFS) is launched at the Paris One Planet Summit (OPS) on December 2017. Its 8 founding members are Banco de Mexico, BoE, Banque de France, Dutch Central Bank, Deutsche Bundesbank, Swedish FSA, Hong Kong Monetary Authority (HKMA), Monetary Authority of Singapore (MAS) and The People’s Bank of China (PBOC). As of October 3rd 2022, the NGFS consists of 121 members and 19 observers25. In addition to its mythological publications, the NGFS is well known for its database on climate scenarios26.

Sustainable finance is not only regulated by financial regulators. In Figures 1.6 and 1.7, we have reported charts from the MSCI website, that list the ESG regulations by type of regulatory agency or by type of regulated party. We observe that the number of regulations is greater for issuers than investors. Moreover, other bodies than financial regulators are involved in the ESG regulation landscape, especially governments. For instance, the French law “Climat et Résilience” (climate and resilience) of 22 August 2021 translates part of the 146 proposals of the Citizen’s Climate Convention adopted by the French government, to reduce greenhouse gas emissions by 40% by 2030 in a spirit of social justice. In Europe, most of ESG regulations are defined by the European Commission (EC) and the European Parliament. This is for example the case of the EU Non-Financial Reporting Directive (NFRD, 2014), the EU Taxonomy Regulation for sustainable activities (EUTR, 2020) and the EU Sustainable Finance Disclosure Regulation (SFDR, 2021). All these policy initiatives are part of the “European Green Deal”, whose aim is making the European Union climate neutral in 2050. New legislations on the circular economy, building renovation, biodiversity, farming and innovation are under way. To define these directives, the EC is supported by technical working groups such as the High-Level Expert Group on sustainable finance (HLEG) or the Technical Expert Group on sustainable finance (TEG). For example, the EC has mandated in 2020 the European Financial Reporting Advisory Group (EFRAG) to undertake preparatory work for the elaboration of the new EU Corporate Sustainability Reporting Directive (CSRDR) that will amend the current NFRD.

25 Including BIS, BCBS, ESM, FSB, IAIS, IMF, IOPS, IOSCO and OECD.

Handbook of Sustainable Finance
Figure 1.6: Who will regulate ESG? — The regulators viewpoint (MSCI, 2022)


Figure 1.7: Who will regulate ESG? — The regulated viewpoint (MSCI, 2022)

1.3.4 Reporting frameworks

As we have already seen, reporting is a key element to understand ESG and climate policies of issuers and investors. In the past 20 years, we are seeing more and more new reporting frameworks. In Table 1.3, we list the best-known ones. For each reporting, we give the creation date of the initiative and the implementation date of the standards. The two first reporting frameworks were those of the Global Reporting Initiative (GRI) and the GHG Protocol. The most recent is the International Sustainability Standards Board (ISSB). In what follows, we distinguish sustainability general reporting and climate specific reporting.

<table>
<thead>
<tr>
<th>Perimeter</th>
<th>Acronym</th>
<th>Name</th>
<th>Dates</th>
</tr>
</thead>
<tbody>
<tr>
<td>General</td>
<td>GC</td>
<td>UN Global Compact Initiative</td>
<td>2000/2000</td>
</tr>
<tr>
<td></td>
<td>GRI</td>
<td>Global Reporting Initiative</td>
<td>1997/2000</td>
</tr>
<tr>
<td></td>
<td>IIRC</td>
<td>International Integrated Reporting Council</td>
<td>2010/2013</td>
</tr>
<tr>
<td></td>
<td>ISSB</td>
<td>International Sustainability Standards Board</td>
<td>2021/2023</td>
</tr>
<tr>
<td></td>
<td>SASB</td>
<td>Sustainability Accounting Standards Board</td>
<td>2011/2016</td>
</tr>
<tr>
<td></td>
<td>SDGs</td>
<td>UN Sustainable Development Goals</td>
<td>2015/2016</td>
</tr>
<tr>
<td>Climate</td>
<td>CDP</td>
<td>Carbon Disclosure Project</td>
<td>2000/2000</td>
</tr>
<tr>
<td></td>
<td>CDSB</td>
<td>Climate Disclosure Standards Board</td>
<td>2007/2015</td>
</tr>
<tr>
<td></td>
<td>PCAF</td>
<td>Partnership for Carbon Accounting Financials</td>
<td>2019/2020</td>
</tr>
<tr>
<td></td>
<td>SBTi</td>
<td>Science Based Targets initiative</td>
<td>2015/2015</td>
</tr>
<tr>
<td></td>
<td>TCFD</td>
<td>Task Force on Climate-Related Financial Disclosures</td>
<td>2015/2017</td>
</tr>
</tbody>
</table>

Sustainability reporting

**International Sustainability Standards Board** After a decade of framework proliferation, the landscape of sustainability reporting has changed significantly over the past two years. In June 2021, SASB and IIRC definitively merged into one organization to form the Value Reporting Foundation (VRF). On 3 November 2021, the IFRS Foundation Trustees announced the creation of the International Sustainability Standards Board (ISSB) chaired by Emmanuel Faber, with the objective to deliver a comprehensive global baseline of sustainability-related disclosure standards. On 31 January 2022, the Climate Disclosure Standards Board (CDSB) was consolidated into the IFRS Foundation to support the work of ISSB. On 1 August 2022, the IFRS Foundation completes a new consolidation with VRF. Even if the previous frameworks continue to exist and can still be used by companies, it will exist only one sustainability reporting standard in the future.

On 31 March 2022, ISSB published the drafts of its first proposed standards:

- IFRS S1 general requirements for disclosure of sustainability-related financial information (ISSB, 2022a);
- IFRS S2 climate-related disclosures (ISSB, 2022b).

The IFRS S1 draft requires companies to identify sustainability-related risks and opportunities until the SASB standards are replaced by IFRS Sustainability Disclosure Standards. The IFRS S2 draft...

---

27Emmanuel Faber was CEO and Chair of the Board at multi-national food products company Danone.
builds on the TCFD recommendations. On October 2022, the ISSB decided to include the scope 3 GHG emissions in the climate reporting according to the fifteen scope 3 categories described in the GHG Protocol.

**Sustainable Development Goals**  The SDGs are a collection of 17 interlinked global goals designed to be a “blueprint to achieve a better and more sustainable future for all”. They were set up in 2015 by the United Nations and are intended to be achieved by 2030. The 17 SDGs are given in Table 1.4.

![The SDGs icons](https://sdgs.un.org/goals#icons).

Each goal is defined by specific targets, and the progress toward each target is measured by indicators. A total of 69 targets and 231 unique indicators are then considered. The numbering system Goal.Target.Indicator is used to structure the tree map of the SDGs. For instance, the first target of the first goal is: 1.1 — By 2030, eradicate extreme poverty for all people everywhere, currently measured as people living on less than $1.25 a day. This target is measured by only one indicator: 1.1.1 — Proportion of the population living below the international poverty line by sex, age, employment status and geographic location. The fifth target of the first goal is: 1.5 — By 2030, build the resilience of the poor and those in vulnerable situations and reduce their exposure and vulnerability to climate-related extreme events and other economic, social and environmental shocks and disasters. This target is measured by three indicators: 1.5.1 — Number of deaths, missing persons and directly affected persons attributed to disasters per 100,000 population, 1.5.2 — Direct economic loss attributed to disasters in relation to global gross domestic product and 1.5.3 — Number of countries that adopt and implement national disaster risk reduction strategies in line with the Sendai Framework for Disaster Risk Reduction 2015-2030. Initially, the SDGs are built for assessing the progress of each country on the different pillars. We can then analyze the evolution of each indicator per country and year. Synthetic scores are also available at the country or goal level. A compilation of these scores can be found in Sachs et al. (2022).  

28They are also available at the web page [https://dashboards.sdgindex.org](https://dashboards.sdgindex.org).
Table 1.4: The 17 SDGs

<table>
<thead>
<tr>
<th>#</th>
<th>Name</th>
<th>Description</th>
<th>E</th>
<th>S</th>
<th>G</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>No poverty</td>
<td>End poverty in all its forms everywhere</td>
<td>✓</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>Zero hunger</td>
<td>End hunger, achieve food security and improved nutrition and promote sustainable agriculture</td>
<td></td>
<td>✓</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>Good health and well-being</td>
<td>Ensure healthy lives and promote well-being for all at all ages</td>
<td></td>
<td>✓</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>Quality education</td>
<td>Ensure inclusive and equitable quality education and promote lifelong learning opportunities for all</td>
<td></td>
<td>✓</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>Gender equality</td>
<td>Achieve gender equality and empower all women and girls</td>
<td></td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>6</td>
<td>Clean water and sanitation</td>
<td>Ensure availability and sustainable management of water and sanitation for all</td>
<td></td>
<td>✓</td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>Affordable and clean energy</td>
<td>Ensure access to affordable, reliable, sustainable and modern energy for all</td>
<td></td>
<td>✓</td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>Decent work and economic growth</td>
<td>Promote sustained, inclusive and sustainable economic growth, full and productive employment and decent work for all</td>
<td></td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>9</td>
<td>Industry, innovation and infrastructure</td>
<td>Build resilient infrastructure, promote inclusive and sustainable industrialization and foster innovation</td>
<td></td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>10</td>
<td>Reduced inequality</td>
<td>Reduce inequality within and among countries</td>
<td></td>
<td>✓</td>
<td></td>
</tr>
<tr>
<td>11</td>
<td>Sustainable cities and communities</td>
<td>Make cities and human settlements inclusive, safe, resilient and sustainable</td>
<td></td>
<td>✓</td>
<td></td>
</tr>
<tr>
<td>12</td>
<td>Responsible consumption and production</td>
<td>Ensure sustainable consumption and production patterns</td>
<td></td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>13</td>
<td>Climate action</td>
<td>Take urgent action to combat climate change and its impacts</td>
<td></td>
<td>✓</td>
<td></td>
</tr>
<tr>
<td>14</td>
<td>Life below water</td>
<td>Conserve and sustainably use the oceans, seas and marine resources for sustainable development</td>
<td></td>
<td>✓</td>
<td></td>
</tr>
<tr>
<td>15</td>
<td>Life on land</td>
<td>Protect, restore and promote sustainable use of terrestrial ecosystems, sustainably manage forests, combat desertification, and halt and reverse land degradation and halt biodiversity loss</td>
<td></td>
<td>✓</td>
<td></td>
</tr>
<tr>
<td>16</td>
<td>Peace, justice, and strong institutions</td>
<td>Promote peaceful and inclusive societies for sustainable development, provide access to justice for all and build effective, accountable and inclusive institutions at all levels</td>
<td></td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>17</td>
<td>Partnerships for the goals</td>
<td>Strengthen the means of implementation and revitalize the Global Partnership for Sustainable Development</td>
<td></td>
<td></td>
<td>✓</td>
</tr>
</tbody>
</table>

Source: https://sdgs.un.org/goals.
Chapter 1. Introduction

The SDGs has been quickly used by financial institutions as a framework for impact investing. In Table 1.4, we map the 17 SDGs and the 3 ESG pillars. Therefore, we can assign the SDGs targets to each ESG dimension. An example applied to artificial intelligence companies is provided by Sætra (2022). The SDGs have also been used to evaluate the ESG objectives of sustainable financial products. For example, ICMA has published a mapping29 to SDGs for green and social bonds (ICMA, 2022), where targets are associated with GBP and SBP categories.

Climate reporting

GHG Protocol The GHG Protocol has been created by WRI and WBCSD in 1998 with the aim of “establishing comprehensive global standardized frameworks to measure and manage greenhouse gas emissions from private and public sector operations, value chains and mitigation actions”. First published in 2001, the standard defines the accounting and reporting of six greenhouse gases covered by the Kyoto Protocol, including carbon dioxide (CO2) and methane (CH4).

The GHG Protocol corporate standard classifies a company’s greenhouse gas emissions in three scopes (GHG Protocol, 2004):

• Scope 1 denotes direct GHG emissions occurring from sources that are owned and controlled by the issuer.

• Scope 2 corresponds to the indirect GHG emissions from the consumption of purchased electricity, heat or steam.

• Scope 3 are other indirect emissions (not included in scope 2) of the entire value chain.

Scope 2 emissions can be computed using two methods30 (GHG Protocol, 2015):

1. the energy mix of the countries (location-based);

2. the energy mix of the utility companies supplying the electricity (market-based).

Scope 3 is based on 15 sub-categories (GHG Protocol, 2011, 2013), which are divided into two main categories31:

• Upstream scope 3 emissions are defined as indirect carbon emissions related to the upstream value chain. More precisely, the upstream scope 3 is based on 8 sub-categories: (1) purchased goods and services, (2) capital goods, (3) fuel and energy related activities, (4) upstream transportation and distribution, (5) waste generated in operations, (6) business travel, (7) employee commuting and (8) upstream leased assets.

• Downstream scope 3 emissions are defined as indirect carbon emissions related to the downstream value chain. They correspond to these next 7 sub-categories: (9) downstream transportation and distribution, (10) processing of sold products, (11) use of sold products, (12) end-of-life treatment of sold products, (13) downstream leased assets, (14) franchises and (15) investments.

Scope 1 emissions are also called direct emissions, whereas indirect emissions encompass both scope 2 and 3 GHG emissions. Unlike scope 1 and 2, scope 3 is an optional reporting category.


30The exact definitions are the following: “a location-based method reflects the average emissions intensity of grids on which energy consumption occurs (using mostly grid-average emission factor data), while “a market-based method reflects emissions from electricity that companies have purposefully chosen (or their lack of choice)”.

31The upstream value chain includes all activities related to the suppliers whereas the downstream value chain refers to post-manufacturing activities.

Handbook of Sustainable Finance
Carbon Disclosure Project  The CDP (formerly the Carbon Disclosure Project) is a UK-based not-for-profit charity co-founded by Paul Dickinson and Tessa Tennant in 2000. CDP runs a global disclosure system for investors, companies, cities, states and regions to manage their environmental impacts. Each year, CDP sends a questionnaire to organizations and collects information on three environmental dimensions:

1. Climate change (based on the GHG Protocol).
2. Forest management;
3. Water security.

In particular, the CDP database is extensively used to measure the carbon footprint of companies, cities and governments. In 2022, more than 18,700 companies and 1,100 cities, states and regions have filled in the questionnaire. This represents half of global market capitalization. Nevertheless, more than 29,500 companies (20% of market capitalization) didn’t respond to the disclosure request.

Remark 1 As CDP is the most comprehensive reporting database for carbon emissions, the CDP data are extensively used by commercial data providers (e.g., Trucost and MSCI) when providing carbon footprint estimates.

TCFD  The Task Force on Climate Related Financial Disclosures (TCFD) is established by the FSB in 2015 to develop a set of voluntary and consistent disclosure recommendations for use by companies in providing information to investors, lenders and insurance underwriters about their climate-related financial risks. The TCFD consists of 31 members from the G20, representing both preparers and users of financial disclosures and is chaired by Michael Bloomberg. The TCFD framework is published in June 2017 and the 11 recommendations are structured around 4 core elements: (1) governance, (2) strategy, (3) risk management, and (4) metrics and targets (Table 1.5). The first core element describes the organization’s governance around climate-related risks and opportunities, whereas the second one lists the actual and potential impacts of climate-related risks and opportunities on the organization’s businesses, strategy, and financial planning. The processes used by the organization to identify, assess, and manage climate-related risks are specified in the risk management tag. Finally, the last core element defines the metrics and targets used to measure and manage relevant climate-related risks and opportunities. The implementation of the reporting framework is extensively described in TCFD (2021a,b), and many examples can be found in CDSB (2021c) and TCFD (2022).

Contrary to the other climate frameworks (e.g., GHG Protocol and CDP), the TCFD framework is a risk reporting, and not only a carbon emission reporting. For instance, we report below some examples of recommended metrics (TCFD, 2022, pages 16-17):

- GHG emissions (absolute scope 1, scope 2, and scope 3 GHG emissions; financed emissions by asset class; weighted average carbon intensity);

---

32The global budget of CDP is about $30 mn. CDP’s funding comes mainly from philanthropic grants (32%), service based memberships (30%) and government grants (12%).

33The differences between the GHG Protocol and CDP reporting templates are the following. The GHG Protocol reporting is more focused on figures, while the CDP reporting contains more open questions and comments. Moreover, the CDP reporting is a little more comprehensive, because it also concern forest management and Water security.

34It is available at https://www.cdp.net/en/data.

35The fact that the CDP reporting is an Excel file may explain that it had more success than the GHG Protocol reporting, which is a Word file. However, they are very similar regarding carbon emissions disclosure.
Table 1.5: The 11 recommended disclosures (TCFD, 2017)

<table>
<thead>
<tr>
<th>Recommendation</th>
<th>#</th>
<th>Recommended Disclosure</th>
</tr>
</thead>
<tbody>
<tr>
<td>Governance</td>
<td>1</td>
<td>Board oversight</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>Management’s role</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>Risks and opportunities</td>
</tr>
<tr>
<td>Strategy</td>
<td>4</td>
<td>Impact on organization</td>
</tr>
<tr>
<td></td>
<td>5</td>
<td>Resilience of strategy</td>
</tr>
<tr>
<td>Risk management</td>
<td>6</td>
<td>Risk ID and assessment processes</td>
</tr>
<tr>
<td></td>
<td>7</td>
<td>Risk management processes</td>
</tr>
<tr>
<td></td>
<td>8</td>
<td>Integration into overall risk management</td>
</tr>
<tr>
<td>Metrics and targets</td>
<td>9</td>
<td>Climate-related metrics</td>
</tr>
<tr>
<td></td>
<td>10</td>
<td>Scope 1, 2, 3 GHG emissions</td>
</tr>
<tr>
<td></td>
<td>11</td>
<td>Climate-related targets</td>
</tr>
</tbody>
</table>


- Transition risks (volume of real estate collaterals highly exposed to transition risk; concentration of credit exposure to carbon-related assets; percent of revenue from coal mining);

- Physical risks (number and value of mortgage loans in 100-year flood zones; revenue associated with water withdrawn and consumed in regions of high or extremely high baseline water stress; proportion of property, infrastructure, or other alternative asset portfolios in an area subject to flooding, heat stress, or water stress; proportion of real assets exposed to 1:100 or 1:200 climate-related hazards);

- Climate-related opportunities (net premiums written related to energy efficiency and low-carbon technology; revenues from products or services that support the transition to a low-carbon economy; proportion of green buildings);

- Capital deployment (percentage of annual revenue invested in R&D of low-carbon products/services; investment in climate adaptation measures);

- Internal carbon prices (internal carbon price, shadow carbon price);

- Remuneration (portion of employee’s annual discretionary bonus linked to investments in climate-related products; weighting of climate goals on long-term incentive; scorecards for executive directors).

Similarly, targets are also more general, and are not limited to carbon emission reduction. For instance, they can concern the amount of executive management remuneration impacted by climate considerations by 2025, the internal carbon price by 2030, the amount invested in green buildings by 2035, etc.

Remark 2 Examples of TCFD reporting are given in Figure 1.9. We can generally find TCFD and climate reports by using the Google search bar with the keywords year + “TCFD report” + corporate name or year + “climate report” + corporate name. As we can observe, the formats of TCFD reports are diverse. They can correspond to a powerpoint file or a written document, the number of pages ranges from 3 to 100, etc.
The TCFD framework is supported by many international bodies and supervisors: European Commission, IFRS, IOSCO, Singapore Exchange Regulation, Central Bank of Brazil, Australian Prudential Regulatory Authority, Canadian Securities Administrators, etc. In this context, it has become the most popular reporting framework from the viewpoint of regulation. Nevertheless, much progress remains to be done, since this reporting is voluntary and not mandatory. For fiscal year 2021 reporting, “80% of companies disclosed in line with at least one of the 11 recommended disclosures; however, only 4% disclosed in line with all 11 recommended disclosures and only around 40% disclosed in line with at least five” (TCFD, 2022, page 5). The average level of disclosure is 60% for European companies, 36% for Asia Pacific companies and 29% for North American companies. Nearly 50% of asset managers and 75% of asset owners reported information aligned with at least five of the 11 recommended disclosures. The most popular recommended disclosures were (#3) risks and opportunities (61%), (#4) impact on organization (47%), and (#9) climate-related metrics (47%), while the less popular items were (#5) resilience of strategy (16%), (#2) management’s role (22%) and (#1) board oversight (29%).
1.3.5 Rating agencies and data providers

To implement ESG strategies, we need extra-financial data. In the 1980s and 1990s, several research companies were then established to provide research on responsible investing. These small-sized firms are generally specialized on a specific dimension and a region. Some of them are focused on the environmental pillar, but the majority of them are specialized in the social pillar. In addition to research and advisory activities, they begin to collect a lot of extra-financial data and build sustainable scores. After an initial period of expansion and innovation, they structure themselves as global rating agencies using the model of credit rating agencies (CRA). Then, we observe a concentration in this industry and a period of consolidation in the 2010s.

The early stage of extra-financial rating agencies

In 2001, the French observatory centre for the corporate social responsibility ORSE published a guide of entities specialized in ESG analysis (ORSE, 2001). This guide has been updated several times until 2012. For instance, in the 2005 edition, ORSE listed 34 sustainable research organizations of which 25 are located in Europe, 5 in North America and 4 in the rest of the world (Australia, Japan, South Korea). This number does not change much during the 2000s. Indeed, most of extra-financial rating agencies were created in the 1990s. Here is a list of some well-know entities:

- Ethical Investment Research Services Ltd. (Eiris, 1983, UK)
- Institutional Shareholder Services (ISS, 1985, UK)
- Kinder, Lydenberg, Domini & Co. (KLD, 1988, US)
- Jantzi Research (Jantzi Research, 1992, Canada)
- Global Engagement Services (GES, 1992, Sweden)
- Innovest Strategic Value Advisors (Innovest, 1995, US)
- Jantzi Research (Jantzi Research, 1992, Canada)
- Global Engagement Services (GES, 1992, Sweden)
- Innovest Strategic Value Advisors (Innovest, 1995, US)
- RepRisk (RepRisk, 1998, Switzerland)
- Oekom Research AG (Oekom, 1999, Germany)
- Ethix SRI Advisors (Ethix, 1999, Sweden)
- Trucost Plc (Trucost, 2000, UK)
- Inrate (Inrate, 2001, UK)

---

[36] The French name is Observatoire de la Responsabilité Sociétale des Entreprises.
[37] This list is based on the works of Eccles and Stroehle (2018) and the company profiles provided by ORSE (2007).
[38] The date of creation and the country are provided in parentheses.
[39] EIRIS was founded in 1983 by charities and churches as the UK’s first independent research service for ethical investors.
[40] Institutional Shareholder Services was originally founded in 1985 by Robert Monks, an ESG advocate. It began to provide voting services in 1992.
[41] KLD was founded in 1989 by Amy Domini, Peter Kinder and Steve Lydenberg to offer institutional investors social research on US companies. In May 1990, it launched the Domini 400 Social Index (DSI).
[44] Innovest was created by Matthew Kierman and Hewson Batzell as “a green analogy to Moody’s” (Eccles et al., 2020). In the first years, it focused on environmental screening. Later, it created the IVA ratings using the credit-like rating scale (AAA, AA, A, BBB, BB, B, and CCC).
[47] The environmental publishing house ökom was founded in 1989. In 1993, ökom GmbH was created for providing environmental research. Ökom research AG became independent in 1999 and focused on corporate responsibility ratings.
[49] Trucost was established in 2000 to help organisations, investors and governments understand and quantify the environmental impacts of business activities. The Trucost’s database was launched later and began with the 2005 financial year.
[50] Inrate is officially created in 2001, but its roots dated back to 1990 with the foundation of Centre Info.
Chapter 1. Introduction

2001, Switzerland), Vigeo (Vigeo\textsuperscript{54}, 2002, France), Dutch Sustainability Research (DSR\textsuperscript{52}, 2002, Netherlands), EthiFinance (EthiFinance\textsuperscript{53}, 2004, France).

The consolidation of the industry

As shown by Eccles and Stroehle (2018) and Demartini (2020), we are seeing a consolidation period in the 2010s. Here are some examples:

- Vigeo and Eiris merged in October 2015 to form Vigeo-Eiris (V.E), which is acquired by Moody’s in April 2019.

- In September 2015 and March 2018, ISS acquired Ethix SRI Advisors and Oekom to form ISS ESG solutions (ISS-ethix, ISS-climate and ISS-oekom). In November 2020, ISS is majority owned by Deutsche Börse Group.

- In February and November 2009, RiskMetrics acquired Innovest and KLD. RiskMetrics is bought by MSCI in 2010, which creates MSCI ESG Research LLC.

- In September 2009, DSR and Jantzi Research merged to form Sustainalytics. In the 2010s, Sustainalytics acquired Responsible Research (Singapore), ESG Analytics (Switzerland), Solaron (India) and GES (Sweden). In April 2020, Sustainalytics becomes a wholly-owned subsidiary of Morningstar.


Today, the industry of extra-financial analysis and ESG ratings is dominated by ISS-Oekom, MSCI, Refinitiv\textsuperscript{54}, Reprisk, S&P Global, Sustainalytics and Moody’s.

Remark 3 In Chapter 2, we will see that these ESG rating agencies are specialized and do not provide the same solutions. For instance, on controversy risk, the major players are MSCI, Reprisk and Sustainalytics. On climate risk, CDP, MSCI and Trucost are the leader agencies, while Verisk Maplecroft is the specialized agency in sovereign ESG risk.

Remark 4 Even if we observe a consolidation, this does not mean that we observe a convergence of ESG methodologies (Chatterji et al., 2016; Berg et al., 2022). This point will be discussed in the next chapter.

The current business of extra-financial data

As noticed by Demartini (2020), the industry is mainly made up of large Anglo-Saxon companies (US and UK) and small European start-up firms. More precisely, we can classify them into three main categories:

\textsuperscript{51}Founded in 1997, Arese was the first SRI rating agency in France. In June 2002, it became Vigeo and was lead-managed by Nicole Notat, the former secretary general of the labor union CFDT. In June 2005, Vigeo merged with the Belgian agency Ethibel.

\textsuperscript{52}DSR was the research team of Triodos Bank, a Dutch niche player in sustainable finance founded in 1980. In 2008, it changed its name and became Sustainalytics.

\textsuperscript{53}EthiFinance was founded in 2004. In 2017, it merged with Spread Research.

\textsuperscript{54}Refinitiv is the former financial and risk unit of Thomson Reuters (including Eikon and Datastream). It is now part of the London Stock Exchange Group (LSEG), which has also acquired FTSE Russell (and Beyond Ratings).
1. Market data providers
   This category comprises financial information providers (Bloomberg, Morningstar), index
   sponsors (Bloomberg, FTSE Russell, MSCI, Solactive) and stock exchanges (LSEG, Deutsche
   Börse Group).

2. Financial rating agencies
   Moody’s, S&P Global and Fitch are now involved in the ESG landscape.

3. Specialized ESG companies
   In this category, we generally find some pioneer companies such as Inrate, ISS ESG, RepRisk
   and Sustainalytics.

4. Technology start-up firms
   Most of new entrants use artificial intelligence (AI), big data, natural language processing
   (NLP), sentiment analysis and quantitative approaches. Some examples are Arabesque, Co-
   valence, OWL ESG, and Truvalue Labs.

This explains the discrepancy between the companies in terms of ESG analysts. About 20% of extra-
financial rating agencies have more than 200 ESG analysts\(^{55}\), while 30% have less than 20 analysts
(Demartini, 2020, page 11). Another difference concerns the wide scope of activities: provision of raw
data, provision of processed data (indicators, scores and ratings), production of ESG indexes, ESG
screening, portfolio analysis, normative analysis, ESG controversy tracking, engagement monitoring,
proxy advisory services, consultancy, etc. (Demartini, 2020). These activities explain that the
business model of extra-financial rating is based on the investor-pays principle, contrary to credit
rating agencies whose historical model was mainly driven by the issuer-pays principle. This means
that investors pay a fee to access data, but issuers don’t pay to be rated.

The question of certification and supervision is on everyone’s lips. For instance, credit rating
agencies registered in the EU are supervised by ESMA\(^ {56}\) (Regulation 462/2013/EU and Directive
2013/14/EU). In the US, the Office of Credit Ratings (OCR) assists the Security and Exchange
Commission (SEC) to oversight those registered as nationally recognized statistical rating organiza-
tions\(^ {57}\) (NRSRO). As the market of ESG ratings is expected to grow, the supervision of this industry
and the protection of investors are becoming an unavoidable topic. For instance, on April 2022, the
EC launched a targeted consultation on the functioning of the ESG rating market in the European
Union and on the consideration of ESG factors in credit ratings (EC, 2022a). The summary report
based on 204 responses\(^ {58}\) is published in August 2022. Its main conclusions are the following:

“The large majority of respondents (over 84%) consider that the market is not function-
ing well today. On the quality of ESG ratings, two thirds of respondents consider the
quality to be fine to very good, with about one third considering it poor. A large majority
of respondents (83%) consider that the lack of transparency on the methodologies used
by the providers is a problem in the ESG ratings market. The vast majority of respon-
dents (91%) also consider that there are significant biases with the methodology used
by providers [...] Almost all respondents (94%) consider that intervention is necessary,

---

\(^{55}\) For instance, Sustainalytics has more than 800 ESG analysts (source: [https://www.sustainalytics.com/about-us](https://www.sustainalytics.com/about-us)).

\(^{56}\) The list of certified CRAs is available at [https://www.esma.europa.eu/supervision/credit-rating-agencies/risk](https://www.esma.europa.eu/supervision/credit-rating-agencies/risk).

\(^{57}\) The list of certified NRSROs is available at [https://www.sec.gov/ocr/ocr-current-nrsros.html](https://www.sec.gov/ocr/ocr-current-nrsros.html).

\(^{58}\) Including 21 ESG rating providers, 48 rating users (investors), 49 rated companies and 18 rating users (company).
of which the large majority (80%+) support a legislative intervention with the remainder supporting the development of non-regulatory intervention in the form of guidelines, code of conduct. Respondents largely indicated (90%+) that the main element to be addressed by the intervention should be improving transparency on the methodology used by ESG rating provider [...] The vast majority of respondents (82%) consider that ESG rating providers should be subject to some form of authorisation/registration regime in order to offer their services in the EU.” (EC, 2022b, pages 3-4).

These results confirm previous analyzes that found that the most common shortcomings are (1) a lack of coverage, (2) data quality, and (3) a lack of transparency around methodologies used by ESG rating providers (Boffo and Patalano, 2020). We can then anticipate that supervisors will certainly introduce regulatory safeguards for using ESG ratings in the near future.

1.4 Regulatory framework

The number of ESG regulations has dramatically increased over the last years. In Figure 1.10, we report its global evolution and the breakdown by region. According to PRI (2022b), there are 868 policy tools and guidance around the world, which encourage or require investors to consider ESG factors. Most of them have been developed since 2000, and we observe an acceleration which coincides with the Paris Agreement for climate change. The breakdown by region is reported in Figure 1.11. We observe that ESG regulations have gained the greatest momentum in Europe, but they are increasing in the other regions too. By analyzing the PRI’s regulation database, we obtain the following results:

- Policies are mainly issued by governments and regulators (78.8%). 19% are released by industry associations, including stock exchanges. Finally, less than 3% are due to international organisations (OECD, UN, ILO, etc.).
- Most of these policies are mandatory. Nevertheless, the number of voluntary-based approaches is significant since they represent 33.2% of the sample.
- Four types of policy dominate: corporate ESG disclosure (61.5%), investor ESG disclosure (24.2%), investor ESG integration (20.3%) and national sustainable finance strategy (10.8%). The other types are sector specific policy (5.6%), financial products (4.5%), stewardship code (2.6%) and taxonomy (1.6%).
- The application of these policies mainly concern corporations (72.4%), asset owners (60.9%), investment managers (40%) and insurance companies (28.2%). The other categories are financial service providers (16.2%) and credit rating agencies (6.5%).
- If we focus on countries, we obtain the following ranking: China (49 policies), Germany (31), European Union (29), Italy (28), Spain (26), France (24), US (23), Netherlands (22), Japan (22) and UK (20).

Most of policies are national. They can also concern a specific sector. For instance, if we focus on regulations aiming to promote the improvement of the energy performance of buildings, and their

---

For each item, we indicate the frequency in %. Since each policy can concern several items, the frequencies may not add up to 100%. For example, a policy can be applicable to both asset owners, issuers and asset managers.

Especially when they are issued by the industry.bodies.

This category include green bonds, social bonds, green labels, etc.
Chapter 1. Introduction

Figure 1.10: Total number of ESG regulations


Figure 1.11: Number of ESG regulations per region

reduction of GHG emissions and energy consumption, we find many legislative policies, for example
the Energy Performance of Buildings Directive (EPBD) in Europe, the French high environmental
quality (HQE) certification, the German buildings energy act (Gebäudeenergiegesetz or GEG), the
German sustainable building certification (Deutsche Gesellschaft für Nachhaltiges Bauen or DGNB),
the Italian energy-efficient construction and renovation certification (CasaClima), the Spanish cli-
mate change and energy transition law, etc. In this context, it is not realistic to have an overview
of the regulations in the World. This is why we will focus on the European Union.

The European regulatory framework is articulated around a set of policy initiatives by the
European Commission:

- The action plan on sustainable finance (May 2018);
- The European Green Deal (December 2019);
- The Fit-for-55 package (July 2021);
- The REPowerEU plan or energy security package (May 2022).

In December 2016, the EC established a high-level expert group on sustainable finance (HLEG),
consisted of 20 senior experts. HLEG (2018) published its final report on 31 January 2018 with
several recommendations and proposals: (1) a classification system (or taxonomy) to provide market
clarity on what is sustainable, (2) clarifying the duties of investors when it comes to achieving a more
sustainable financial system, (3) improving disclosure by financial institutions and companies on
how sustainability is factored into their decision-making, (4) an EU-wide label for green investment
funds, (5) making sustainability part of the mandates of the European Supervisory Authorities
(ESAs) and (6) a European standard for green bonds. All these recommendations are endorsed
by the EC and form the basis of the action plan on sustainable finance adopted by the EC in
on sustainable finance (TEG) is established to assist the EC in developing an EU green taxonomy
(1), guidance to improve corporate disclosure of climate-related information (3), an EU green bond
standard (6) and methodologies for EU climate benchmarks. In December 2019, the EC proposed
a set of climate change policies, including biodiversity, circular economy, construction, energy, food,
forests, transport, etc. The overarching aim of this European Green Deal is for the European
Union to become the world’s first climate-neutral continent by 2050. To finance this climate change
strategy, the EC adopted in July 2021 the Renewed Sustainable Finance Strategy, which is a package
of measures to help improve the flow of money towards financing the transition to a sustainable
economy. The goal is to mobilize at least €1 tn financing over the decade. At the same time, a new
cycle of legislative package are proposed under the European Green Deal framework. In particular,
the EC adopted the Fit-for-55 package, a set of policies to reach the objective of cutting GHG
emissions by 55% by 2030 versus 1990. The plan relies on four pillars:

1. a more pronounced industrial transformation, with a wider application of the EU Emissions
Trading System (ETS) to new sectors, along with a tightening of the ETS itself;

---

62 We will not speak about the situation in the US, because it is not stabilized, in particular with the recent emergence of the anti-ESG movement. The subject apparently seems to be highly controversial. On May 25, 2022, the US Securities and Exchange Commission (SEC) proposed new rules and reporting forms to enhance the regulatory framework for disclosures concerning funds’ and advisers’ incorporation of ESG factors. Nevertheless, these rules are still under discussion. At the same time, we observe US political moves against ESG investing (e.g., Texas, Florida). Therefore, these backlashes place the US in an uncertain ESG environment.

63 With existing measures, the EU’s carbon emissions are expected to fall 36% only below 1990 levels.

64 Emissions trading systems are presented in Chapter 8 on page 316.
2. a faster transition to clean mobility and air transport;
3. a significant growth of renewable energies\textsuperscript{65} and energy efficiency;
4. the restoration of natural ecosystems and forestry to absorb carbon from natural sinks.

On 18 May 2022, the EC published the REPowerEU plan that contains a suite of measures to phase out Russian fossil fuels by 2027 and boost the EU’s renewable energy production and energy efficiency measures. The REPowerEU plan is presented as “the response of the EC to the hardships and global energy market disruption caused by Russia’s invasion of Ukraine”. The objective is clearly to cut the gas dependency of the European Union. It is also an extension project of the Fit-for-55 package with four objectives: energy savings, diversifying supplies, accelerating the rollout of renewable energies and reducing fossil fuel consumption in industry and transport.

\textbf{Remark 5} The European Green Deal, the Fit-for-55 package and the REPowerEU plan forms the global climate strategy of the European Union. At first sight, we may think that they concern almost exclusively climate investing, and not ESG investing. Nevertheless, the EU climate strategy supports a just transition mechanism. According to ILO, “a just transition means greening the economy in a way that is as fair and inclusive as possible to everyone concerned, creating decent work opportunities and leaving no one behind”. This implies that the S and G pillars of ESG factors cannot be disregarded. For instance, to ensure a socially fair transition, the EC proposed to create a social climate fund of €144.4 bn. The objective of this fund is to protect the poorest citizens that are most impacted by energy and mobility costs.

The implementation timeline, which is reported in Figures 1.12 and 1.12, demonstrates that the European ESG regulation is a continuous work in progress, implying that most of frameworks discussed below are not finished or can change.

\textbf{1.4.1 EU taxonomy regulation}

The purpose of a green financial taxonomy is to define what is green, and its objective is to inform investors about the greenness of their investments. Therefore, they can evaluate whether these levels satisfy or not their expectations. According to the European Commission\textsuperscript{66}, the EU taxonomy for sustainable activities is “a classification system, establishing a list of environmentally sustainable economic activities. […] The EU taxonomy would provide companies, investors and policymakers with appropriate definitions for which economic activities can be considered environmentally sustainable. In this way, it should create security for investors, protect private investors from greenwashing, help companies to become more climate-friendly, mitigate market fragmentation and help shift investments where they are most needed”. In this context, the EU taxonomy is a common base for other ESG regulations (BMR, SFDR, MiFID II, IDD, CSRD), acting as a “common language” around sustainable economic activities.

Developed by the Technical Expert Group on sustainable finance (TEG, 2020), the EU green taxonomy defines economic activities which make a substantive contribution to at least one of the following six environmental objectives:

1. Climate change mitigation

\textsuperscript{65}The target of renewables share is set to 40% in 2030.

\textsuperscript{66}See the EU website: \url{https://ec.europa.eu/info/business-economy-euro/banking-and-finance/sustainable-finance_en}. 

\textit{Handbook of Sustainable Finance}
Chapter 1. Introduction

Figure 1.12: Sustainable finance — implementation timeline (Reference ESMA34-45-1580)

Chapter 1. Introduction

Figure 1.13: Sustainable finance — implementation timeline (Reference ESMA34-45-1580)

Corporate Sustainability Reporting Directive (CSRD) - Final text
UCITS and AIFMD DAs
MiFID and IDD DAs
SDR RTs - Joint ESMA draft Regulatory Technical Standards (RTS) LNG
Sustainable Finance Disclosures Regulation (SFDR) L1
Taxonomy Regulation Article 8 Delegated Act (DA)
Taxonomy Regulation (TR) L1

Legend

ESAs Report on voluntary corporate sustainability reports under SFDR
EESAs Report on voluntary evaluation reports
European Commission

Implementation timeline for SFDR | TR | CSRD | UCITS | AIFMD | MiFID | IDD | TR?
To qualify as sustainable, a business activity must also meet two other criteria. Indeed, the activity must do no significant harm to the other environmental objectives (DNSH constraint) and comply with minimum social safeguards (MS constraint). Figure 1.14 summarizes the different steps.

Figure 1.14: EU taxonomy for sustainable activities

1a. SC Substantially contribute to at least one of the six objectives

1b. TSC Comply with Technical Screening Criteria

2. DNSH Do No Significant Harm to any other five objectives

3. MS Comply with Minimum (Social) Safeguards

In Table 1.6, we have reported the activities eligible for the first two environmental objectives (climate change mitigation and climate change adaptation). For instance, the activity “Human health and social work activities” is eligible for the adaptation objective, but not for the mitigation objective. For each activity, we have also indicated the number of sub-activities that are concerned. For instance, the activity “Financial and insurance activities” has only two eligible sub-activities: #10.1 Non-life insurance: underwriting of climate-related perils and #10.2 Reinsurance. For each sub-activity, the taxonomy also indicates the corresponding NACE sectors, and the different criteria (technical screening and DNSH) for the eligibility certification.

67 For example, the UN guiding principles on business and human rights.

68 The finalization of the four other environmental objectives is expected on 1 January 2023 (Figure 1.12).

69 When there are two numbers, the first one is for the mitigation objective whereas the second concerns the adaptation objective.

70 NACE is the industry standard classification system used in the European Union. It is the abbreviation for the French term “Nomenclature statistique des Activités économiques dans la Communauté Européenne” (in English, statistical classification of economic activities in the European Community).

71 All these informations can be found in the EU Taxonomy Compass Excel file, which corresponds to Annex 1 and Annex 2 of the Delegated Act on the climate objectives (Delegated Regulation2021/2139 of 4 June 2021).
Table 1.6: Activities eligible for the first two objectives (mitigation and adaptation)

<table>
<thead>
<tr>
<th>Activity name</th>
<th>#</th>
<th>Objective (1)</th>
<th>Objective (2)</th>
<th>Activity number</th>
</tr>
</thead>
<tbody>
<tr>
<td>Arts, entertainment and recreation</td>
<td>13</td>
<td>✓</td>
<td>✓</td>
<td>3</td>
</tr>
<tr>
<td>Construction and real estate</td>
<td>7</td>
<td>✓</td>
<td>✓</td>
<td>7</td>
</tr>
<tr>
<td>Education</td>
<td>11</td>
<td>✓</td>
<td></td>
<td>1</td>
</tr>
<tr>
<td>Energy</td>
<td>4</td>
<td>✓</td>
<td>✓</td>
<td>31</td>
</tr>
<tr>
<td>Environmental protection and restoration activities</td>
<td>2</td>
<td>✓</td>
<td>✓</td>
<td>1</td>
</tr>
<tr>
<td>Financial and insurance activities</td>
<td>10</td>
<td>✓</td>
<td></td>
<td>2</td>
</tr>
<tr>
<td>Forestry</td>
<td>1</td>
<td>✓</td>
<td></td>
<td>4</td>
</tr>
<tr>
<td>Human health and social work activities</td>
<td>12</td>
<td>✓</td>
<td></td>
<td>1</td>
</tr>
<tr>
<td>Information and communication</td>
<td>8</td>
<td>✓</td>
<td>✓</td>
<td>2/3</td>
</tr>
<tr>
<td>Manufacturing</td>
<td>3</td>
<td>✓</td>
<td></td>
<td>17</td>
</tr>
<tr>
<td>Professional, scientific and technical activities</td>
<td>9</td>
<td>✓</td>
<td>✓</td>
<td>3/2</td>
</tr>
<tr>
<td>Transport</td>
<td>6</td>
<td>✓</td>
<td>✓</td>
<td>17</td>
</tr>
<tr>
<td>Water supply, sewerage, waste management and remediation</td>
<td>5</td>
<td>✓</td>
<td>✓</td>
<td>12</td>
</tr>
</tbody>
</table>


Remark 6 The EU Taxonomy Regulation cannot be reduced to a green taxonomy. Indeed, the environmental taxonomy is the most advanced area, but the objective is to cover other topics. In particular, the development of brown and social taxonomies are currently discussed by the EC and European regulators.

1.4.2 Climate benchmarks

In September 2019, the EU Technical Expert Group on sustainable finance (TEG) proposed to create two climate benchmark labels\footnote{According to the TEG (2019a), “a climate benchmark is defined as an investment benchmark that incorporates — next to financial investment objectives — specific objectives related to greenhouse gas (GHG) emission reductions and the transition to a low-carbon economy through the selection and weighting of underlying benchmark constituents”.}: climate transition benchmark (CTB) and Paris aligned benchmark (PAB). These labels are structured along the following common principles:

1. A year-on-year self-decarbonization of 7% on average per annum, based on scope 1, 2 and 3 emissions;
2. A minimum carbon intensity reduction $R^-$ compared to the investable universe;
3. A minimum exposure to sectors highly exposed to climate change.

For the CTB label, the minimum reduction $R^-$ is set to 30% whereas it is equal to 50% for the PAB label. Other constraints are also imposed such as issuer exclusions (controversial weapons and societal norms violators), a minimum green revenue share ratio (or green-to-brown ratio\footnote{The implementation of GRS or GTB ratios is delayed, because it requires a comprehensive definition of green/brown taxonomies.}) or some activity exclusions. These climate labels are now part of the EU Benchmarks Regulation (BMR), which also specifies ESG disclosure requirements for all benchmarks\footnote{With the exception of interest rate and currency benchmarks.}. In particular, an index sponsor must disclose whether its benchmarks pursue ESG objectives and provide an explanation of the methodology incorporating ESG factors used by these benchmarks.
1.4.3 Sustainable finance disclosure regulation

The SFDR is a European disclosure regulation\textsuperscript{75} that applies at entity level and product level. It concerns websites of financial market participants (Article 4), remuneration policies in relation to the integration of sustainability risks (Article 5), the disclosure of principal adverse impacts (Article 7), the promotion of ESG on websites (Article 10), and periodic and annual reports (Article 11). The disclosure level depends on the ESG degree of the product and the following product/fund classification:

- Article 6 (or non-ESG products)
  It covers standard financial products that cannot be Article 8 or Article 9.

- Article 8 (or ESG products)
  It corresponds to financial products which “promote, among other characteristics, environmental or social characteristics, or a combination of those characteristics, provided that the companies in which the investments are made follow good governance practices”.

- Article 9 (or sustainable products)
  In addition to the points covered by Article 8, these financial products have a sustainable investment objective.

For Article 8 and Article 9 products, the SFDR implies the disclosure of qualitative and quantitative ESG information (ex-ante requirements for KIID, prospectus and websites, and ex-post requirements for annual reports and MiFID client reports). In particular, pre-contractual documents need to indicate ex-ante minimum and planned percentage of sustainable investment (SI) according to following breakdown:

- SI with environmental objective
  - in economic activities that are taxonomy-aligned
  - in economic activities that are not taxonomy-aligned

- SI with social objective

They also need to indicate how the portfolio manager takes into account principal adverse impacts (PAI). Among the 64 PAI indicators, some of them are mandatory while other are voluntary. In Table 1.7, we report the 18 mandatory PAI indicators, which depend on the investment type (exposure on corporations, investment on sovereign and supranational securities, real estate assets). Beside these mandatory indicators, the SFDR RTS\textsuperscript{76} also defines 22 and 24 optional PAI indicators for \( E \) and \( S \) pillars\textsuperscript{77}.

The first level (SFDR Level 1) has come into effect on 10 March 2021. It required FMPs to disclose general SFDR information at entity level and SFDR classification at product level. On 1st


\textsuperscript{76}In European Union, a Regulatory Technical Standard RTS is a delegated act, technical, prepared by a European Supervisory Authority. It should further develop, specify and determine the conditions for consistent harmonisation of the rules included in the basic legislative act. For instance, the SFDR RTS has been developed by ESMA, EBA, EIOPA and the ESAs’ Joint Committee.

\textsuperscript{77}The comprehensive list of PAI indicators and their associated metrics is given in Chapter 4 on page 203.

\textsuperscript{78}Final Report on draft Regulatory Technical Standards with regard to the content, methodologies and presentation of disclosures pursuant to Article 2a(3), Article 4(6) and (7), Article 8(3), Article 9(5), Article 10(2) and Article 11(4) of Regulation (EU) 2019/2088
Table 1.7: The 18 mandatory PAI indicators

<table>
<thead>
<tr>
<th>Corporates</th>
</tr>
</thead>
<tbody>
<tr>
<td>Climate and other environment-related indicators</td>
</tr>
<tr>
<td>1 GHG emissions</td>
</tr>
<tr>
<td>2 Carbon footprint</td>
</tr>
<tr>
<td>3 GHG intensity of investee companies</td>
</tr>
<tr>
<td>4 Exposure to companies active in the fossil fuel sector</td>
</tr>
<tr>
<td>5 Share of non renewable energy consumption and production</td>
</tr>
<tr>
<td>6 Energy consumption intensity per high impact climate sector</td>
</tr>
<tr>
<td>7 Activities negatively affecting biodiversity sensitive areas</td>
</tr>
<tr>
<td>8 Emissions to water</td>
</tr>
<tr>
<td>9 Hazardous waste ratio</td>
</tr>
<tr>
<td>Social and employee, respect for human rights, anti-corruption and anti-bribery matters</td>
</tr>
<tr>
<td>10 Violations of UN Global Compact principles and OECD Guidelines for Multi-national Enterprises</td>
</tr>
<tr>
<td>11 Lack of processes and compliance mechanisms to monitor compliance with UN Global Compact principles and OECD Guidelines for MNEs</td>
</tr>
<tr>
<td>12 Unadjusted gender pay gap</td>
</tr>
<tr>
<td>13 Board gender diversity</td>
</tr>
<tr>
<td>14 Exposure to controversial weapons (anti personnel mines, cluster munitions, chemical weapons and biological weapons)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Sovereigns and supranationals</th>
</tr>
</thead>
<tbody>
<tr>
<td>Climate and other environment-related indicators</td>
</tr>
<tr>
<td>15 GHG intensity</td>
</tr>
<tr>
<td>Social and employee, respect for human rights, anti-corruption and anti-bribery matters</td>
</tr>
<tr>
<td>16 Investee countries subject to social violations</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Real estate assets</th>
</tr>
</thead>
<tbody>
<tr>
<td>Climate and other environment-related indicators</td>
</tr>
<tr>
<td>17 Exposure to fossil fuels through real estate assets</td>
</tr>
<tr>
<td>18 Exposure to energy-inefficient real estate assets</td>
</tr>
</tbody>
</table>

Source: SFDR RTS\textsuperscript{78} (2 February 2021).

January 2023, SFDR Level 2 comes into effect, implying the publication of PAI indicators for Article 8 and Article 9 products. PAI reporting at the entity level for year 2022 must be published in June 2023.

Since August 2022, financial advisors (FAs) have to assess the sustainability preferences of their clients (MiFID II & IDD). For that, FinDatEx has developed the European ESG Template (EET) in order to facilitate the exchange of ESG-related data between market participants. The EET is an Excel file that contains qualitative information (e.g., fund’s name, isin, currency, SFDR classification) and quantitative data, especially PAI indicators and taxonomy figures. The EET could be viewed as a SFDR/Taxonomy template.

1.4.4 MiFID II and sustainable preferences

MiFID is the Markets in Financial Instruments Directive (2004/39/EC). It has been applicable across the European Union to investment advice and portfolio management activity since November 2007.
Its aim is to standardize practices across the EU for investment services and activities and to ensure a high degree of harmonised protection for investors in financial instruments. MiFID II is a revised version of the original MiFID and came into force in 2018. It covers organisational requirements for investment firms, regulatory reporting to avoid market abuse, OTC trading, transparency of costs, etc.

Concerning investor protection, financial advisors must make a suitability and appropriateness assessment for individual portfolio management or advice regarding financial instruments. This implies FAs must obtain information from the client before it provides investment advice or individual portfolio management. The MiFID II Suitability Test includes questions about investors’ knowledge and experience, their financial position, and their investment objectives. In September 2022, ESMA has published its guidelines on integrating ESG risks and factors in MiFID II (ESMA, 2022). There are two main consequences:

1. Integration of sustainability preferences to define the suitable product;
2. Integration of ESG criteria in the product governance.

The first point ensures that the product is in line with investors’ values when providing financial advice and portfolio management services. This implies a new version of the suitability and appropriateness assessment (profiling questionnaire, suitability test, adequacy report). The second point covers the product offering of FMPs. Indeed, manufacturers and distributors must specify their target markets and the sustainability-related objectives with which the product is compatible.

“Sustainability preferences” is the key concept when selling an ESG product. If the client has any sustainability preferences (yes/no), it has to choose one or a combination of the criteria below:

1. Minimum percentage in environmentally sustainable investments aligned to the EU Taxonomy.
2. Minimum percentage invested in sustainable investments as defined in the SFDR (Articles 8 and 9).
3. Quantitative/qualitative elements of principal adverse impacts defined by the client.

Once the choice is done, the financial adviser can sell a product to the client only after ensuring that the product matches the sustainability preferences of the client.

**Remark 7** The integration of sustainability preferences is not limited to financial investment products and MiFID II. It also applies to insurance-based investment products and the Insurance Distribution Directive (IDD).

### 1.4.5 Corporate sustainability reporting directive

The Corporate Sustainability Reporting Directive (CSRD) makes mandatory for corporates to disclose sustainability information in their financial reports. It applies to all listed companies in the EU and all large European companies meeting at least two of the following criteria: (1) 250 employees, (2) €40 mn turnover and (3) €20 mn total assets. This represents about 50,000 corporates and 75% of total corporates’ turnover in the EU. The CSRD will replace the NFRD and is planned to come into effect on 1 January 2025. According to EFRAG (2022), the sustainable reporting standards shall taking into account the following topics:

79Client’s sustainability preferences are required since August 2022.
• Environmental factors: (1) climate change mitigation; (2) climate change adaptation; (3) water and marine resources; (4) resource use and circular economy; (5) pollution; (6) biodiversity and ecosystems.

• Social factors: (1) equal opportunities for all; (2) working conditions; (3) respect for human rights.

• Governance factors: (1) role and composition of administrative, management and supervisory bodies; (2) business ethics and corporate culture, including anti-corruption and anti-bribery; (3) political engagements of the undertaking, including its lobbying activities; (4) management and quality of relationships with business partners.

For the environmental factors, we recognize the 6 objectives of the green taxonomy. It is no coincidence, given that CSRD must be in line with SFDR and EUTR. In fact, it must help financial institutions to compute the ESG and climate metrics in a more robust and effective manner. Beside current KPIs, the CSRD also requires the company to measure and assess its targets. For instance, this type of forward-looking information is helpful for investors to define their net zero investment policies. Nevertheless, the CSRD has another ambition by considering double materiality. It is a first step in developing a comprehensive extra-financial/climate accounting statement. Materiality is an accounting principle which states that an information on a company is material if it is reasonably likely to impact investors’ decision-making. This is why it must be recorded or reported in financial statements. It is now widely accepted that climate-related impacts on a company can be material and therefore require disclosure. This approach is called financial or single materiality. The concept of double materiality is an extension of the single materiality by also considering the negative externalities of the company. In this case, we must consider two materiality perspectives:

- How sustainable factors impact the financial value of the company?
- How the company affects the environment, the society and people?

The first one corresponds to the financial (or outside-in) materiality, while the second defines the impact (or inside-out) materiality. For example, the SASB framework is based on the financial materiality. On the contrary, the GRI framework has adopted an inside-out materiality by reporting companies’ impact on people and the planet. In the case of the CSRD, EFRAG has made the choice to consider the double materiality assessment.

1.5 The market of ESG investing

In this section, we present a global overview of the ESG market from the investment viewpoint. First, we define the different ESG strategies and provide some examples. Then, we give some figures about the ESG market and its growth.

1.5.1 ESG strategies

In Figure 1.15, we define the different types of ESG strategies. This list is based on several reports (Eurosif, 2018; GSIA, 2021; PRI, 2020). Depending on the region and the organization, these strategies can be categorized and adapted to specific needs.
Chapter 1. Introduction

Figure 1.15: The 7 categories of ESG strategies

1. Exclusion
   - Exclusion policy & negative (or worst-in-class) screening

2. Values
   - Norms-based screening

3. Selection
   - Positive (or best-in-class) screening

4. Thematic
   - Sustainability themed investing (e.g. green bonds)

5. Integration
   - ESG scoring is fully integrated in portfolio management

6. Engagement
   - Voting policy & shareholder activism

7. Impact
   - Impact investing


Table 1.8: Comparison of Eurosif, GSIA and PRI classifications

<table>
<thead>
<tr>
<th>#</th>
<th>Eurosif</th>
<th>GSIA</th>
<th>PRI</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Exclusions</td>
<td>Negative/exclusionary screening</td>
<td>Negative screening</td>
</tr>
<tr>
<td>2</td>
<td>Norms-based screening</td>
<td>Norms-based screening</td>
<td>Norms-based screening</td>
</tr>
<tr>
<td>3</td>
<td>Best-in-class</td>
<td>Best-in-class/positive screening</td>
<td>Positive screening</td>
</tr>
<tr>
<td>4</td>
<td>Sustainability themed</td>
<td>Sustainability themed/thematic investing</td>
<td>Thematic</td>
</tr>
<tr>
<td>5</td>
<td>ESG integration</td>
<td>ESG integration</td>
<td>Integration of ESG issues</td>
</tr>
<tr>
<td>6</td>
<td>Engagement &amp; voting</td>
<td>Corporate engagement &amp; shareholder action</td>
<td>Engagement/proxy voting</td>
</tr>
<tr>
<td>7</td>
<td>Impact investing</td>
<td>Impact/community investing</td>
<td>Sustainability impact</td>
</tr>
</tbody>
</table>

Handbook of Sustainable Finance
categories can take different names. For instance, in the case of the seventh category, the term “community investing” is extensively used in North America (RIA Canada, US SIF), while we prefer the term “microfinance” in Europe.

Most of these categories are based on the screening concept, which refers to investment filters. Negative screening is an approach that excludes specific investments or classes of investment from the investible universe such as companies, sectors, or countries that do not comply with specific ESG criteria. When applied to companies, it is also called the worst-in-class exclusion strategy. In this case, the investor can systematically exclude issuers that have the worst rating grade (e.g., companies rated CCC). This category also concerns sector or sub-industry exclusion (e.g., coal & consumable fuels, fossil fuels production, conventional weapons, civilian firearms). This approach can also include certain activities, because they do not comply with the values of the investor (e.g., pornography, tobacco, alcohol, gambling, genetically modified). Most of the time, the investor define an exclusion list of individual issuers.

Norm-based screening consists in excluding companies that have been called into question because they have violated international standards and norms on social or environmental issues, such as those issued by the OECD, ILO, UN Global Compact and UNICEF. The first category is closed to this second category, but this later is based on international values while the former is based on individual values. For instance, a company, which complies with all the minimum standards of business practice based on international norms, can be excluded in the negative screening approach because it has a very bad ESG rating or it belongs to a sector that the investor does not want to finance. By considering the first two categories, the top exclusion criteria in Europe are (1) controversial weapons (Ottawa and Oslo treaties), (2), tobacco, (3) all weapons, (4) gambling, (5) pornography, (6) nuclear energy, (7) alcohol, (8) GMO and (9) animal testing (Eurosif, 2018).

The third category invests in issuers, sectors, or projects selected for positive ESG performance relative to industry peers. This is why the selection category is also called the positive screening approach. For example, the best-in-class ESG strategy selects issuers with the best ESG ratings (e.g. AAA, AA and A), while the ESG momentum strategy selects issuers that have improved their ESG rating.

The aim of sustainability themed investing is to invest in companies whose activity is related to sustainability, for example clean energy, green technology, sustainable agriculture, sustainable infrastructure, natural resources, biodiversity. ESG thematic investing considers all the ESG issues, not only the environmental pillar. For example, it concerns investment in social topics (e.g., health, food security, diversity) and governance topics (e.g., gender equality, inclusive boards). Generally, these thematic investments are implemented in mutual funds.

ESG integration means the systematic and explicit inclusion by investment managers of ESG factors into financial analysis and asset allocation. This strategy can be viewed as an extension of the exclusion and best-in-class strategies. For example, the stock or bond picking score may be a mix of the fundamental score and the ESG score. Some asset managers also impose funds to have an ESG score greater than the ESG score of their benchmarks.

The sixth category uses shareholder power and active ownership to influence corporate behavior, including through direct corporate engagement (i.e., communicating with senior management and/or boards of companies), filing or co-filing shareholder proposals, and proxy voting that is guided by ESG guidelines. Examples of engagement activities are voting policy, public divestment, engagement with target companies on a specific subject (e.g., pay ratio, living wage), proposing shareholder resolutions, public litigation, etc.

81Genetically modified organism.
Impact investing are investments made with the intention to generate positive, measurable social and environmental impact alongside a financial return. Contrary to thematic investing which mainly considers stocks and bonds of companies, impact investing considers assets and securities financing specific projects. For example, impact investing includes microfinance, community investing, social entrepreneurship funds, funds with a social impact objective, green and social bonds. Since the goal is to achieve positive, social and environmental impacts, this requires measuring and reporting against these extra-financial impacts. Extra-financial reporting is then the key element of impact investing, because it must clearly define and measure the ESG objectives (e.g., GHG avoided emissions per €1 mn invested per year, percentage of water consumption saving).

Remark 8 We notice that these seven categories can be split into two strategy groups. The first one considers ESG scores when building an investment portfolio (exclusion, selection, thematic and integration). The main objective of these strategies remains the financial performance of the portfolio. The second group places a high priority on ethical conduct (norm-based screening, engagement and impact investing) and can be related to the signaling theory. In this approach, investors send a negative signal to the market and corporations when they apply norm-based screening or they engage with a company. On the contrary, investors send a positive signal when they implement impact investing.

1.5.2 The market share of ESG investing

In this section, we present a global view of the market growth of ESG investing based on the Global Sustainable Investment Reviews (GSIA, 2017, 2019, 2021). For each report, Figures 1.16, 1.17 and 1.18 gives the AUM of responsible investing, the corresponding market share, the global growth and the breakdown by countries. For each report. According to GSIA (2021), sustainable investments represented $35.3 tn of assets under management at the start of 2020, representing a market share of 36%. They are continuing to grow in most regions, with Canada experiencing the largest increase (48% growth), followed by the United States (42% growth). If we consider a regional analysis, the regional market share of sustainable investments is equal to 62% in Canada, 42% in Europe, 38% in Australasia, 33% in the United States and 24% in Japan.

Remark 9 The case of Europe (13% decline in the growth of sustainable investment assets in 2018 to 2020) is due to a changed measurement methodology from which European data are collected, and European regulations, especially the SFDR. Therefore, we must be cautious before drawing conclusions. Indeed, these data do not take into account how ESG factors are really implemented.

Figure 1.19 shows changes in asset values by ESG categories. For many years, negative screening and exclusion dominates the other strategies. Since 2020, ESG integration has become the most implemented approach. We also notice that some categories are less represented: thematic investing, best-in-class/selection and impact investing. However, we observe that thematic investing is the category with the highest growth of asset values.

If we focus on asset ownership, the ESG market is mainly driven by institutional investors. They currently represent 75% of the market, while the remaining part (25%) corresponds to retail assets. Nevertheless, we observe a basic shift, because the split was 89%/11% in 2012 (GSIA, 2021, page 13).

---

82Because the investor is not satisfied by the environmental, social or governance policies of the company.

83The figures concerning specific segments (mutual funds, ETFs, green financing, etc.) are given in Chapters 2 and 10.

84In the last study period, but also since 2014.
Chapter 1. Introduction

Figure 1.16: Sustainable investment assets at the start of 2016

- **USA**: $8.7 tn, 33% growth in 2 years
- **Canada**: $1.1 tn, 49% growth in 2 years
- **Japan**: $480 bn (vs $7 bn in 2014)
- **Australia / NZ**: $500 bn, 247% growth in 2 years


Figure 1.17: Sustainable investment assets at the start of 2018

- **USA**: $12.0 tn, 38% growth in 2 years
- **Canada**: $1.7 tn, 42% growth in 2 years
- **Japan**: $2.2 tn (vs $474 bn in 2016)
- **Australia / NZ**: $0.7 tn, 46% growth in 2 years

Source: GSIA (2019).
Figure 1.18: Sustainable investment assets at the start of 2020

$35.3tn Global RI market in 2020
35.9% of total global AUM
+15% Growth in 2 years


Figure 1.19: Asset values of ESG strategies between 2014 and 2018

Chapter 1. Introduction

Table 1.9: ESG asset growth

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Exclusion</td>
<td>11.7%</td>
<td>14.6%</td>
<td>−24.0%</td>
<td>15 030</td>
</tr>
<tr>
<td>2</td>
<td>Values/Norms-based</td>
<td>19.0%</td>
<td>−13.1%</td>
<td>−11.5%</td>
<td>4 140</td>
</tr>
<tr>
<td>3</td>
<td>Selection</td>
<td>7.6%</td>
<td>50.1%</td>
<td>−24.9%</td>
<td>1 384</td>
</tr>
<tr>
<td>4</td>
<td>Thematic Investing</td>
<td>55.1%</td>
<td>92.0%</td>
<td>91.4%</td>
<td>1 948</td>
</tr>
<tr>
<td>5</td>
<td>Integration</td>
<td>17.4%</td>
<td>30.2%</td>
<td>43.6%</td>
<td>25 195</td>
</tr>
<tr>
<td>6</td>
<td>Engagement</td>
<td>18.9%</td>
<td>8.3%</td>
<td>6.8%</td>
<td>10 504</td>
</tr>
<tr>
<td>7</td>
<td>Impact Investing</td>
<td>56.8%</td>
<td>33.7%</td>
<td>−20.8%</td>
<td>352</td>
</tr>
</tbody>
</table>


1.6 Conclusion

This little-boring introduction gives a global overview of the sustainable landscape. As a student, you need to understand who does what, the outlines of the different regulations and some figures about sustainable finance. Nevertheless, a course in sustainable finance cannot only be summarized by a series of acronyms (Figure 1.20). We also need to understand the data that we manipulate. Moreover, since data are very noisy and non-exhaustive, probability and quantitative modeling is important for two main reasons. The first one is to assess the limits of what professionals are doing. The second reason is to measure the relationships between the several factors from an ex-ante viewpoint, and to forge some convictions because data and numbers can lie to us.

Figure 1.20: The ESG world of acronyms
Part I

ESG Risk
Chapter 2

ESG Scoring

To develop ESG analysis, we need extra-financial data that are provided by companies, reporting frameworks, scientific institutes, research centers, international bodies, etc. Generally, these heterogeneous data are collected by ESG data providers. These data are available for two levels of use. First, they are extensively used by ESG analysts to assess the sustainability risks of companies and countries. Second, they form the raw material of ESG scoring systems. Like credit scoring models, such systems have paramount importance for risk assessment and decision-making. In the case of credit scoring, the issue is to decide whether or not to give credit. This is why credit scoring models are at the centre of the credit-granting process. In the case of ESG scoring, the issue is a little bit different. Of course, we can use ESG scores to decide whether or not to invest in a company, but exclusion is not the only strategy as we have seen in the previous chapter. For instance, ESG scores are fully embedded within the strategy of ESG integration. In this approach, they play the role of screening rules for portfolio selection. Therefore, ESG scoring is more than a traditional scoring model. Nevertheless, the analogy between ESG scoring and credit scoring remains essential and implies several challenges in terms of performance evaluation, score consistency and backtesting. This is particularly true because ESG risk ratings are produced from these scoring systems. In this perspective, the concept of ESG model validation takes a new dimension. We remind that any internal risk model must comply with an independent model validation process, which is highly binding and formal from a regulation viewpoint (FRB, 2011; EBA, 2022). Moreover, the validation process does not just apply to credit, market, operational and liquidity risks. For instance, it also concerns compliance risks: statistical models developed for anti-money laundering detection, transaction monitoring, anomaly detection scenarios, list filtering, etc. The systematic validation approach of any model (risk-based, behavior-based, rules-based and AI-based) has been recently reinforced in the US with the interagency guidance on model risk management (FRB, 2021). As ESG scoring models are more and more used by financial institutions, we can easily predict that they will be regulated in a near future as the other risk models. Therefore, I adopt in this chapter the underlying idea that a scoring system must be validated from an ex-post viewpoint. For that, I extensively use the mathematical and statistical tools that we encounter in the fields of scoring theory and Markov-based rating methods (Roncalli, 2020a, Section 3.3.3 and Chapter 15). This chapter is then organized as follows. Section 1 presents the ESG data and the sources of extra-financial information. The construction of ESG scores and the performance evaluation of ESG scoring models are discussed in Section 2. Finally, we study ESG rating systems and assess the consistency of ESG migration matrices.
2.1 Data and variables

In this section, we list the most important variables or indicators that are used in an ESG scoring system. For that, we distinguish between sovereign and corporate data since the sources are not the same and their access is more or less easy. As the adage says that “we can only measure what we can define”, we must first specify the meaning of the three ESG factors, because the objective of an ESG score is to measure the risk and opportunities of an entity with respect to environmental, social and governance dimensions. If we consider the definition on page 1, we notice that each factor is defined by encompassing several issues:

- **E** climate change mitigation, climate change adaptation, preservation of biodiversity, pollution prevention, circular economy;
- **S** inequality, inclusiveness, labor relations, investment in human capital and communities, human rights;
- **G** management structure, employee relations, executive remuneration.

Of course, this list is non-exhaustive and must be adapted to show the difference between sovereign and corporate entities. Let us consider an example. According to the Universal Declaration of Human Rights\(^1\), States have obligations and duties under international law to respect, protect and fulfill human rights:

> "The obligation to respect means that States must refrain from interfering with or curtailing the enjoyment of human rights. The obligation to protect requires States to protect individuals and groups against human rights abuses. The obligation to fulfill means that States must take positive action to facilitate the enjoyment of basic human rights."

For a sovereign, the issue of human rights concerns both social (e.g., access to health and education, labor rights) and governance (e.g., safeguarding of civil and political rights) pillars, while it is more related to the social pillar (e.g., ethical supply chain, employment conditions) of a company. Therefore, it is certainly easier to define the three dimensions with examples.

2.1.1 Sovereign ESG data

The World Bank framework

The World Bank database dedicated to sovereign ESG indicators is certainly the easiest way to understand the most common topics relevant to ESG analysis. The database is available at the following webpage: https://datatopics.worldbank.org/esg. It contains 67 ESG indicators grouped into 17 themes. In Table 2.1, we have reported these categories and the corresponding number of indicators. For example, the **E** pillar is made up of 5 categories, such as emissions and pollution that contains 5 indicators. In total, we have 5 **E**, 6 **S** and 6 **G** themes. We observe that global warming and its consequences are the main drivers of the environmental pillar. If we analyse the 27 indicators (Table 2.2), two categories are related to the measurement of climate change (emissions & pollution, environment/climate risk & resilience), one category is related to the mitigation risks of climate change (natural capital endowment & management, energy use & security), and the last category concerns the impact of climate change on food security. If we focus on the **S** pillar, the sources of social risks are related to inclusiveness and inequality (education & skills, poverty & inequality, health & nutrition, access to services), in particular the literacy rate, the school enrollment,

---

\(^1\)See https://www.ohchr.org/en/ohchr_homepage.
Table 2.1: The World Bank database of sovereign ESG indicators

<table>
<thead>
<tr>
<th>Environmental (27)</th>
<th>Social (22)</th>
<th>Governance (18)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Emissions &amp; pollution (5)</td>
<td>Education &amp; skills (3)</td>
<td>Human rights (2)</td>
</tr>
<tr>
<td>Natural capital endowment &amp; management (6)</td>
<td>Employment (3)</td>
<td>Government effectiveness (2)</td>
</tr>
<tr>
<td>Energy use &amp; security (7)</td>
<td>Demography (3)</td>
<td>Stability &amp; rule of law (4)</td>
</tr>
<tr>
<td>Environment/climate risk &amp; resilience (6)</td>
<td>Poverty &amp; inequality (4)</td>
<td>Economic environment (3)</td>
</tr>
<tr>
<td>Food security (3)</td>
<td>Health &amp; nutrition (5)</td>
<td>Gender (4)</td>
</tr>
<tr>
<td></td>
<td>Access to services (4)</td>
<td>Innovation (3)</td>
</tr>
</tbody>
</table>

Table 2.2: Indicators of the environmental pillar (World Bank database)

- **Emissions & pollution**: (1) CO2 emissions (metric tons per capita); (2) GHG net emissions/removals by LUCF (Mt of CO2 equivalent); (3) Methane emissions (metric tons of CO2 equivalent per capita); (4) Nitrous oxide emissions (metric tons of CO2 equivalent per capita); (5) PM2.5 air pollution, mean annual exposure (micrograms per cubic meter);

- **Natural capital endowment & management**: (1) Adjusted savings: natural resources depletion (% of GNI); (2) Adjusted savings: net forest depletion (% of GNI); (3) Annual freshwater withdrawals, total (% of internal resources); (4) Forest area (% of land area); (5) Mammal species, threatened; (6) Terrestrial and marine protected areas (% of total territorial area);

- **Energy use & security**: (1) Electricity production from coal sources (% of total); (2) Energy imports, net (% of energy use); (3) Energy intensity level of primary energy (MJ/$2011$ PPP GDP); (4) Energy use (kg of oil equivalent per capita); (5) Fossil fuel energy consumption (% of total); (6) Renewable electricity output (% of total electricity output); (7) Renewable energy consumption (% of total final energy consumption);

- **Environment/climate risk & resilience**: (1) Cooling degree days (projected change in number of degree Celsius); (2) Droughts, floods, extreme temperatures (% of population, average 1990-2009); (3) Heat Index 35 (projected change in days); (4) Maximum 5-day rainfall, 25-year return level (projected change in mm); (5) Mean drought index (projected change, unitless); (6) Population density (people per sq. km of land area);

- **Food security**: (1) Agricultural land (% of land area); (2) Agriculture, forestry, and fishing, value added (% of GDP); (3) Food production index (2004-2006 = 100);

Table 2.3: Indicators of the social pillar (World Bank database)

- **Education & skills**: (1) Government expenditure on education, total (% of government expenditure); (2) Literacy rate, adult total (% of people ages 15 and above); (3) School enrollment, primary (% gross);

- **Employment**: (1) Children in employment, total (% of children ages 7-14); (2) Labor force participation rate, total (% of total population ages 15-64) (modeled ILO estimate); (3) Unemployment, total (% of total labor force) (modeled ILO estimate);

- **Demography**: (1) Fertility rate, total (births per woman); (2) Life expectancy at birth, total (years); (3) Population ages 65 and above (% of total population);

- **Poverty & inequality**: (1) Annualized average growth rate in per capita real survey mean consumption or income, total population (%); (2) Gini index (World Bank estimate); (3) Income share held by lowest 20%; (4) Poverty headcount ratio at national poverty lines (% of population);

- **Health & nutrition**: (1) Cause of death, by communicable diseases and maternal, prenatal and nutrition conditions (% of total); (2) Hospital beds (per 1,000 people); (3) Mortality rate, under-5 (per 1,000 live births); (4) Prevalence of overweight (% of adults); (5) Prevalence of undernourishment (% of population);

- **Access to services**: (1) Access to clean fuels and technologies for cooking (% of population); (2) Access to electricity (% of population); (3) People using safely managed drinking water services (% of population); (4) People using safely managed sanitation services (% of population);

Table 2.4: Indicators of the governance pillar (World Bank database)

- **Human rights**: (1) Strength of legal rights index (0 = weak to 12 = strong); (2) Voice and accountability (estimate);

- **Government effectiveness**: (1) Government effectiveness (estimate); (2) Regulatory quality (estimate);

- **Stability & rule of law**: (1) Control of corruption (estimate); (2) Net migration; (3) Political stability and absence of violence/terrorism (estimate); (4) Rule of law (estimate)

- **Economic environment**: (1) Ease of doing business index (1 = most business-friendly regulations); (2) GDP growth (annual %); (3) Individuals using the internet (% of population);

- **Gender**: (1) Proportion of seats held by women in national parliaments (%); (2) Ratio of female to male labor force participation rate (%) (modeled ILO estimate); (3) School enrollment, primary and secondary (gross), gender parity index (GPI); (4) Unmet need for contraception (% of married women ages 15-49);

- **Innovation**: (1) Patent applications, residents; (2) Research and development expenditure (% of GDP); (3) Scientific and technical journal articles;

Chapter 2. ESG Scoring

the Gini index\(^2\), the income share held by the lowest 20%, etc. We also notice that the integration of some indicators from the categories employment and demography is disturbing. Indeed, we may wonder how the fertility rate is related to the social pillar. For instance, does a high fertility rate increase or decrease social risk? The \(\mathbb{E}\) pillar includes two classical governance categories (government effectiveness, stability & rule of law), two economic categories (economic development, innovation) and two social-based categories (human rights, gender). In this last case, the frontier between social and governance is blurred. For instance, we can classify the four indicators of the gender category in the social pillar as a non-discrimination category.

**Remark 10** The definition of each indicator can be found on the website [https://datatopics.worldbank.org/esg/framework.html](https://datatopics.worldbank.org/esg/framework.html). Most of these variables are intuitive and easy to understand. Some of them are more technical and less comprehensible, especially some technical variables of the governance pillar. Therefore, we report in footnotes the definition provided by the World Bank for the following indicators: strength of legal rights index\(^3\); voice and accountability\(^4\); government effectiveness\(^5\); regulatory quality\(^6\); rule of law\(^7\).

Certainly, one of the difficulties when building an ESG score is the data gathering, which requires the use of many internal and external sources. In the case of the World Bank framework, the data comes from\(^8\):


---

\(^2\)The Gini index is a measure of income inequality among individuals. It is based on the comparison of cumulative proportions of the population against cumulative proportions of income they receive, and it ranges between 0 in the case of perfect equality and 1 in the case of perfect inequality. Its computation is derived from the Lorenz curve.

\(^3\)“Strength of legal rights index measures the degree to which collateral and bankruptcy laws protect the rights of borrowers and lenders and thus facilitate lending”.

\(^4\)“Voice and accountability captures perceptions of the extent to which a country’s citizens are able to participate in selecting their government, as well as freedom of expression, freedom of association, and a free media”.

\(^5\)“Government effectiveness captures perceptions of the quality of public services, the quality of the civil service and the degree of its independence from political pressures, the quality of policy formulation and implementation, and the credibility of the government’s commitment to such policies”.

\(^6\)“Regulatory quality captures perceptions of the ability of the government to formulate and implement sound policies and regulations that permit and promote private sector development”.

\(^7\)“Rule of law captures perceptions of the extent to which agents have confidence in and abide by the rules of society, and in particular the quality of contract enforcement, property rights, the police, and the courts, as well as the likelihood of crime and violence”.

\(^8\)The list is not exhaustive.

- National agencies and non-governmental organizations: Climate Watch (https://www.climatewatchdata.org), Netherlands Environmental Assessment Agency (PBL, https://www.pbl.nl), World Database on Protected Areas (WDPA, https://www.protectedplanet.net/en/thematic-areas/wdpa);

- Academic resources: Kaufmann et al. (2010), Cohen et al. (2017), and the international disasters database (EM-DAT) of the Centre for Research on the Epidemiology of Disasters (CRED, Université Catholique de Louvain).

Some of these databases are more relevant than others. If we would like to focus on a small number, our preferences are CCKP, EDGAR and Climate Watch for the E pillar, FAO, ILO and WHO for the S pillar, and the Worldwide Governance Indicators (WGI, https://info.worldbank.org/governance/wgi) produced by Daniel Kaufmann and Aart Kraay for the G pillar.

Table 2.5: Sovereign ESG taxonomy

<table>
<thead>
<tr>
<th>Environmental</th>
<th>Social</th>
<th>Governance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Biodiversity &amp; land use</td>
<td>Civil unrest</td>
<td>Business &amp; economic</td>
</tr>
<tr>
<td>CO$_2$e emissions</td>
<td>Demography</td>
<td>environment</td>
</tr>
<tr>
<td>Compliance with</td>
<td>Education</td>
<td>Corruption &amp; money</td>
</tr>
<tr>
<td>environmental standards</td>
<td>Gender</td>
<td>laundering</td>
</tr>
<tr>
<td>Energy security &amp;</td>
<td>Health</td>
<td>Governance effectiveness</td>
</tr>
<tr>
<td>renewables</td>
<td>Income inequality &amp; poverty</td>
<td>Infrastructure and</td>
</tr>
<tr>
<td>Emissions reduction</td>
<td>Labour rights &amp; working</td>
<td>mobility</td>
</tr>
<tr>
<td>targeting</td>
<td>conditions</td>
<td>International relations</td>
</tr>
<tr>
<td>Food security</td>
<td>Living standards</td>
<td>Justice</td>
</tr>
<tr>
<td>Fossil fuel dependency</td>
<td>Migration</td>
<td>National security</td>
</tr>
<tr>
<td>Green economy</td>
<td>Human rights &amp; local</td>
<td>Political stability &amp;</td>
</tr>
<tr>
<td>Physical risk exposure</td>
<td>communities</td>
<td>institutional strength</td>
</tr>
<tr>
<td>Pollution &amp; waste</td>
<td>Non-discrimination</td>
<td>Personal freedom &amp;</td>
</tr>
<tr>
<td>management</td>
<td>Social discrimination</td>
<td>civil liberties</td>
</tr>
<tr>
<td>Temperature</td>
<td>Water cohesion</td>
<td>Rights of shareholders</td>
</tr>
<tr>
<td>Transition risk</td>
<td>Water and electricity</td>
<td>Rule of law</td>
</tr>
<tr>
<td>Water management</td>
<td>access</td>
<td></td>
</tr>
</tbody>
</table>

Source: Author’s research based on the works of Bouyé and Menville (2021), Gratcheva et al. (2020) and Semet et al. (2021).
Other frameworks

Most ESG rating agencies provide sovereign ESG data. The most known are FTSE (Beyond Ratings), Moody’s (Vigeo-Eiris), MSCI, Sustainalytics and RepRisk. One of the most comprehensive databases is certainly Verisk Mapplecroft (https://www.maplecroft.com), which is a global company covering country risk. If we make the union of the different categories, we obtain a taxonomy that looks like the one in Table 2.5. There are many categories, much greater than for the World Bank framework or the PRI taxonomy. If we consider the indicators, the number of variables is large, much greater than 400. Nevertheless, as explained by Bouyé and Menville (2021) and Šmet et al. (2021), they are highly correlated. If we perform a principal component analysis, there are few independent dimensions (less than 10). In fact, many of these indicators are correlated to the GDP. For instance, Gratcheva et al. (2020) found that the average correlation between sovereign ESG scores and national income is equal to 81% for aggregate ESG, 51% for E pillar, 85% for S pillar, and 70% for G pillar. If we consider correlations for ESG providers, the lowest correlations are obtained for the E pillar of ISS (7%), MSCI (10%) and V.E (23%), and the G pillar of RepRisk (37%) and V.E (39%), but they are generally high. Therefore, although all these providers use very different indicators, we notice a relative convergence between them.

Table 2.6: Correlation of ESG scores with country’s national income (GNI per capita)

<table>
<thead>
<tr>
<th>Factor</th>
<th>ESG</th>
<th>E</th>
<th>S</th>
<th>G</th>
</tr>
</thead>
<tbody>
<tr>
<td>ISS</td>
<td>68%</td>
<td>7%</td>
<td>86%</td>
<td>77%</td>
</tr>
<tr>
<td>FTSE (Beyond Ratings)</td>
<td>91%</td>
<td>74%</td>
<td>88%</td>
<td>84%</td>
</tr>
<tr>
<td>MSCI</td>
<td>84%</td>
<td>10%</td>
<td>90%</td>
<td>77%</td>
</tr>
<tr>
<td>RepRisk</td>
<td>78%</td>
<td>79%</td>
<td>75%</td>
<td>37%</td>
</tr>
<tr>
<td>RobecoSAM</td>
<td>89%</td>
<td>82%</td>
<td>85%</td>
<td>85%</td>
</tr>
<tr>
<td>Sustainalytics</td>
<td>95%</td>
<td>83%</td>
<td>94%</td>
<td>93%</td>
</tr>
<tr>
<td>V.E</td>
<td>60%</td>
<td>23%</td>
<td>79%</td>
<td>39%</td>
</tr>
<tr>
<td>Total</td>
<td>81%</td>
<td>51%</td>
<td>85%</td>
<td>70%</td>
</tr>
</tbody>
</table>

Source: Gratcheva et al. (2020, Table 3.1, page 32).

The mushrooming growth of data

We observe among ESG data providers a mushrooming of indicators and data sources. This concerns the first well-established variables. For a very long time, income inequality was mainly measured by the Gini coefficient or the Lorenz curve, even if there were many other academic measures. It seems that data providers have recently rediscovered and embraced the academic literature. Thus, income inequality may also be measured by the Palma ratio, the S80/S20 (or 20:20) ratio, the Atkinson index, the percentile ratios (P90/P10, P90/P50, P50/P10), the Pietra index, the coefficient of variation or the Theil index. Nevertheless, the mushrooming growth of data mainly concerns non-economic variables. We provide some examples in Figures 2.1–2.4 with palm oil production and consumption,

---

9PRI (2019a) identifies 4 environmental factors (natural resources, physical risks, energy transition risk, energy security), 4 social factors (demographic change, education and human capital, living standards and income inequality, social cohesion) and 4 governance factors (institutional strength, political stability, government effectiveness, regulatory effectiveness).

10Gratcheva et al. (2020, Table 2.3, page 27) found that the average cross-correlation between these providers is equal to 85% for the ESG score, 42% for the environmental score, 85% for the social score and 71% for the governance score. These results are confirmed by the study of Bouyé and Menville (2021, Table 4, page 14).
Chapter 2. ESG Scoring

Figure 2.1: Palm oil production (2019)

Figure 2.2: Palm oil imports (2019)
Figure 2.3: Share of global annual deforestation (2015)

Share of global annual deforestation, 2015
The UN FAO publish forest data as the annual average on 10- or 5-year timescales. The following year allocation applies: “1990” is the annual average from 1990 to 2000; “2000” for 2000 to 2010; “2010” for 2010 to 2015; and “2015” for 2015 to 2020.

Source: UN Food and Agriculture Organization (FAO); Forest Resources Assessment. OurWorldInData.org/forests-and-deforestation • CC BY


Figure 2.4: Threatened mammal species (2018)

Threatened mammal species, 2018
Mammal species are mammals excluding whales and porpoises. Threatened species are those classified on the Red List as Critically Endangered, Endangered or Vulnerable. They are at high or greater risk of extinction in the wild.

Source: International Union for Conservation of Nature (via World Bank) CC BY

deforestation and threatened mammal species. In particular, we notice the increasing use of geo-
location data, real-time data, or satellite data, for example, the data provided by the World Resources
Institute (WRI) and its different data platforms (https://www.wri.org/data/data-platforms). The most interesting are Ocean Watch (data on ocean economies and management), Aqueduct (cutting-edge data to identify and evaluate water risks), Global Forest Watch (data on forest economies and management) and LandMark (global data of indigenous and community lands). For instance, we can collect data on coastal eutrophication risk, mangrove extent change, coral reef locations, seagrass, salt marshes, soil erosion, chlorophyll-a concentration, etc.

Figure 2.5: Global living planet index

Source: https://livingplanetindex.org/latest_results & Author’s calculations.

One of the hot topics is currently the biodiversity. A quick search on the web produces dozen of internet pages11. Financial institutions have also launched another initiative: Finance For Biodiversity Pledge (https://www.financeforbiodiversity.org). The UN Biodiversity Conference (COP 15), which is organized by the CBD in Montreal, Canada from 7 to 19 December 2022, has certainly given a special impulse, and may explain this new interest. However, biodiversity loss12 is a very old topic and has been scientifically documented since the 1990s (Cardinale et al., 2012). According to Almond et al. (2022), biodiversity, as measured by the Living Planet Index13, has decreased by 69%

---


12Biodiversity loss describes the decline in the number, genetic variability, and variety of species, and the biological communities in a given area.

13The LPI is computed using a subset of 31,821 populations of 5,230 species and a statistical model (Westveer et al., 2022, page 28-31).
on average since 1970, but with a lot of heterogeneity across regions\textsuperscript{14}. Even if the biodiversity loss has decreased these last years (Figure 2.5), this will inevitably result in negative consequences on global wealth in the long run. The seminal work of Costanza et al. (1997) estimated that the annual economic value of natural capital is on average two times the annual economic value of global GNP, explaining that “ecosystem services provide a significant portion of the total contribution to human welfare on this planet”.

Box 2.1: Ecological diversity indexes

Let $p = (p_1, \ldots, p_{n_S})$ be the proportion vector of species where $p_i$ is the relative abundance\textsuperscript{a} of the $i^{\text{th}}$ specie. The Hill diversity coefficient of order $\eta \geq 0$ is defined as:

$$D^\eta(p) = \left( \sum_{i=1}^{n_S} p_i^\eta \right)^{1/(1-\eta)}$$

We can show that $1 \leq D^\eta(p) \leq n_S$ and the bounds are reached for the 1- and $n$-diversity distributions\textsuperscript{b}, $\pi^-_n$ and $\pi^+_n$. The Hill number measures the “effective number of species”, meaning that the system holds a diversity equivalent to $D^\eta(p)$ equally distributed species. The parameter $\eta$ defines the sensitivity of the true diversity to rare versus abundant species by modifying the weight given to specie abundances. When $\eta = 0$, $D^\eta(p)$ is equal the current number $n_S$ of species or the richness of species. When $\eta \to 1$, we obtain the Shannon diversity index $I^\times(p)$, which is equal to the exponential of the Shannon entropy $I(p)$:

$$D^1(p) = I^\times(p) = \exp(I(p)) = \exp \left( -\sum_{i=1}^{n_S} p_i \ln p_i \right)$$

When $\eta = 2$, we obtain:

$$D^2(p) = \left( \sum_{i=1}^{n_S} p_i^2 \right)^{-1}$$

We recognize the inverse of the Herfindahl index $H(p) = \sum_{i=1}^{n_S} p_i^2$ (also called the Simpson index $\lambda(p)$ in ecology). Finally, when $\eta \to \infty$, the Hill index converges to the proportional abundance of the most abundant specie:

$$D^\infty(p) = \max_i p_i$$

$D^\infty(p)$ is then equal to the infinite norm of $p$.

\textsuperscript{a}It is equal to number of individuals in the $i^{\text{th}}$ specie relative to the total number of individuals in the population.

\textsuperscript{b}See their definition on page 582.

The sudden interest of financial institutions in biodiversity may be explained by climate change, but also by a greater awareness of its critical functions (food security, health, etc.). Moreover, the seventh mandatory PAI indicator requires reporting the share of investments that negatively affect biodiversity sensitive areas\textsuperscript{15}, and the sixth objective of the EUTR is dedicated to the “protec-

\textsuperscript{14}This figure is respectively equal to $-18\%$ in Europe and Central Asia, $-20\%$ in North America, $-55\%$ in Asia and the Pacific, $-66\%$ in Africa, and $-94\%$ in Latin America.

\textsuperscript{15}See Table 1.7 on page 36.
tion and restoration of biodiversity and ecosystem”. All this obviously creates a high demand for biodiversity data and new opportunities for data providers, but as mentioned by Bowker (2000), biodiversity implies data diversity. Again, we are dealing with a huge amount of data\textsuperscript{16}. For example, Icerberg Data Lab\textsuperscript{17} (corporate biodiversity footprint or CBF), Carbon 4 (global biodiversity score\textsuperscript{18} or GBS), CDC Biodiversité (global biodiversity score for financial institutions\textsuperscript{19} or GBSFI), ISS ESG\textsuperscript{20} (mean species abundance or MSA, potentially disappeared fraction of species or PDF) and Verisk Maplecroft (biodiversity and protected areas index score\textsuperscript{21} or BPAI) have already developed biodiversity scores. For countries, most biodiversity data are open source\textsuperscript{22} (Stephenson and Stengel, 2020):

- the Red List Index (RLI, \url{https://www.iucnredlist.org})

The RLI is an index of extinction risk for species of plants and animals. It is computed\textsuperscript{23} by the IUCN and is available for five taxonomic groups: birds, mammals, amphibians, cycads and warm-water reef-forming corals. It can be disaggregated in various ways: subset of species (pollinator species, forest-specialist species, invasive alien species, etc.), country, region, etc.

\textsuperscript{16}And also with a lot of diversity measures (Bandeira et al., 2013; Ohlmann et al., 2019).
\textsuperscript{17}\url{https://icebergdatalab.com}.
\textsuperscript{19}\url{https://www.cdc-biodiversite.fr/le-global-biodiversity-score}.
\textsuperscript{21}\url{https://www.maplecroft.com/insights/analysis/mining-operations-face-growing-biodiversity-risks}.
\textsuperscript{22}See the Guide on Biodiversity Measurement Approaches produced by the Finance for Biodiversity Pledge for a comparison of commercial and open source databases (\url{https://www.financeforbiodiversity.org/publications/guide-on-biodiversity-measurement-approaches}).
\textsuperscript{23}The methodology is described in Butchart et al. (2007).
For instance, we report in Figure 2.6 the aggregate RLI for Brazil, China, France, Poland, La Réunion and US.

- World Database on Protected Areas (WDPA, https://www.protectedplanet.net)
- Integrated Biodiversity Assessment Tool (IBAT, https://www.ibat-alliance.org), including the Species Threat Abatement and Restoration metric (STAR)
- Etc.

Remark 11  Biodiversity risk is a key element for impact investing. We refer to Chapter 5 for an extensive study of this risk (Section 5.4 on page 223).

2.1.2 Corporate ESG data

Compared to sovereign ESG data, the collection, understanding and use of corporate ESG data is much more complicated and requires a lot of time and resources. In the first case, we have about 200 countries in the world, many international organizations that produce country data for decades, and vast academic research on this topic. For instance, the economic literature on income inequality starts in the early twentieth century with the seminal publications of Lorenz (1905) and Gini (1921). Since that time, the number of research studies on income inequality has grown exponentially. In the case of corporate ESG data, data production has just become very recently, and the data dimension is not comparable. According to the World Federation of Exchanges (WFE), there are nearly 58,200 listed companies in the world at the end of Q1 2022. Moreover, data collection is not easier because it has concerned private data for a very long time. It is only recently that extra-financial reporting frameworks for corporate issuers exist, and most of them are voluntary. Finally, the last issue when using corporate ESG data is that most of indicators does not have a universal definition. In a nutshell, there are 3 main challenges and barriers to corporate ESG data:

1. Data coverage (how to collect data for all the listed companies?)
2. Data sourcing (where to find the data?)
3. Data quality (what is the accuracy of the collected data?)

Main indicators

As we have previously seen, we must distinguish several levels of data. Indeed, raw data are generally transformed into ESG metrics, and these metrics are used to define an ESG score. The main difficulty is collecting the raw data. In the case of corporates, this process is time-consuming and manual. The main sources of raw data are:

1. Corporate publications (self-reporting)
   (a) Annual reports
   (b) Corporate sustainability reports

---

24 According to Google scholar, there are more than 5,700 published papers on this topic from 1950 to 1980, and already about 270 before 1950.
2. Financial and regulatory filings (standardized reporting)

   (a) Mandatory reports (SFDR, CSRD, EUTR, etc.)
   (b) Non-mandatory frameworks (PRI, TCFD, CDP, etc.)

For instance, the CDP database is the basic raw material used by all ESG rating agencies for measuring the carbon footprint of issuers. It can be viewed as the entry point and gives a first picture. Then, rating agencies will complete these data by gathering information from annual reports and other sources such as:

3 News and other media

4 NGO reports and websites

5 Company assessment and due diligence questionnaire (DDQ)

For example, S&P Global uses a 230-pages company questionnaire\(^{25}\) called Corporate Sustainability Assessment. At the end of the collection data process, we may have missing data, noisy data or heterogeneous data. Therefore, the data are completed or adjusted by considering internal statistical models, e.g., industry-based clustering methods. This can be considered as a sixth source of data:

6 Internal models

Once these raw data are collected and cleaned, they can be used to calculate ESG metrics (second level of ESG variables). They are then grouped to define ESG indicators (third level of ESG variables), which are combined to form the basic ESG themes (fourth level of ESG variables). In the sequel, an ESG criterion is a generic term to name ESG variables: it may be an ESG metric, an ESG indicator or an ESG theme. Finally, ESG Pillars are generally based on a few number of ESG themes. This slicing method of ESG variables is illustrated in Figure 2.7. ESG rating agencies do not publicly disclose the raw data they use. Generally, they stop on the theme stage, sometimes on the indicator stage. To better understand the slotting method, we report an example of ESG criteria in Table 2.7. In this example, the E and S pillars are made up of 9 environmental themes, 7 social themes and 8 governance themes. Here, we do not have access to the ESG indicators. We

notice that some criteria are global and concerns all the issuers (e.g., carbon emissions), but other are specific to a given industry (e.g., green cars for the automobile sector, green financing for the banking sector). The choice of the themes/indicators will be done by the ESG rating agency, and the distinction between the two levels is not always obvious. For instance, if the board diversity is measured by the male-female ratio, the ESG theme is measured by a single ESG indicator. In this case, it is difficult to make a distinction between the two levels. Another issue concerns the classification of ESG themes. Let us consider the supply chain for example. It is a social issue if we would like to measure whether or not the suppliers of the company respect human rights and labor standards, but it can be an environmental issue if we would like to measure the impact of the suppliers on climate change and pollution. In Table 2.7, we also observe that the choice of ESG themes may be subjective. For example, we can merge the two categories Pollution and Waste disposal into one category Pollution & waste disposal, we can name Corporate ethics instead of Corporate behaviour, we can split Biodiversity into two categories (fauna & wildlife conservation; flora & land management), etc.

Table 2.7: An example of ESG criteria

<table>
<thead>
<tr>
<th>Environmental</th>
<th>Social</th>
<th>Governance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Biodiversity</td>
<td>Access to medicine</td>
<td>Audit and control</td>
</tr>
<tr>
<td>Carbon emissions</td>
<td>Community involvement &amp; human rights</td>
<td>Board diversity</td>
</tr>
<tr>
<td>Green cars*</td>
<td>Customer concern &amp; responsibility</td>
<td>Board independence</td>
</tr>
<tr>
<td>Green financing*</td>
<td>Diversity</td>
<td>Corporate behaviour</td>
</tr>
<tr>
<td>Energy use</td>
<td>Employment conditions &amp; labor standards</td>
<td>CSR strategy</td>
</tr>
<tr>
<td>Pollution</td>
<td>Gender equality</td>
<td>Executive compensation</td>
</tr>
<tr>
<td>Renewable energy</td>
<td>Supply chain</td>
<td>Management compensation</td>
</tr>
<tr>
<td>Waste disposal</td>
<td></td>
<td>Shareholder’ rights</td>
</tr>
<tr>
<td>Water use</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

In what follows, we give some insight into the themes and indicators used by rating agencies. This public information about the ESG criteria has been collected from their website, and varies considerably between providers.

- Bloomberg rates 11,800 public companies. They use more than 120 ESG indicators and 2,000+ data points.
- ISS ESG rates about 10,000 issuers. They use more than 800 indicators and apply approximately 100 indicators per company.

---

26 It is the ratio of men to women or the proportion of women in the company board.
27 E.g., climate change strategy, eco-efficiency, energy management, environmental impact of product portfolio, environmental management, water risk and impact for the pillar; equal opportunities, freedom of association, health and safety, human rights, product responsibility, social impact of product portfolio, supply chain management, taxes for the pillar; business ethics, compliance, independence of the board, voting rights, shareholder participation, remuneration for the pillar.
## Table 2.8: MSCI ESG key issue hierarchy

<table>
<thead>
<tr>
<th>Pillar</th>
<th>#</th>
<th>Theme</th>
<th>#</th>
<th>Indicator</th>
</tr>
</thead>
<tbody>
<tr>
<td>Environment</td>
<td>1</td>
<td>Climate Change</td>
<td>1</td>
<td>Carbon Emissions</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>2</td>
<td>Product Carbon Footprint</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>3</td>
<td>Financing Environmental Impact</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>4</td>
<td>Climate Change Vulnerability</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>Natural Capital</td>
<td>5</td>
<td>Water Stress</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>6</td>
<td>Biodiversity &amp; Land Use</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>7</td>
<td>Raw Material Sourcing</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>Pollution &amp; Waste</td>
<td>8</td>
<td>Toxic Emissions &amp; Waste</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>9</td>
<td>Packaging Material &amp; Waste</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>10</td>
<td>Electronic Waste</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>Environmental Opportunities</td>
<td>11</td>
<td>Opportunities in Clean Tech</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>12</td>
<td>Opportunities in Green Building</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>13</td>
<td>Opportunities in Renewable Energy</td>
</tr>
<tr>
<td>Social</td>
<td>5</td>
<td>Human Capital</td>
<td>14</td>
<td>Labor Management</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>15</td>
<td>Health &amp; Safety</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>16</td>
<td>Human Capital Development</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>17</td>
<td>Supply Chain Labor Standards</td>
</tr>
<tr>
<td></td>
<td>6</td>
<td>Product Liability</td>
<td>18</td>
<td>Product Safety &amp; Quality</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>19</td>
<td>Chemical Safety</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>20</td>
<td>Consumer Financial Protection</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>21</td>
<td>Privacy &amp; Data Security</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>22</td>
<td>Responsible Investment</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>23</td>
<td>Health &amp; Demographic Risk</td>
</tr>
<tr>
<td></td>
<td>7</td>
<td>Stakeholder Opposition</td>
<td>24</td>
<td>Controversial Sourcing</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>25</td>
<td>Community Relations</td>
</tr>
<tr>
<td></td>
<td>8</td>
<td>Social Opportunities</td>
<td>26</td>
<td>Access to Communications</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>27</td>
<td>Access to Finance</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>28</td>
<td>Access to Health Care</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>29</td>
<td>Opportunities in Nutrition &amp; Health</td>
</tr>
<tr>
<td>Governance</td>
<td>9</td>
<td>Corporate Governance</td>
<td>30</td>
<td>Ownership &amp; Control</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>31</td>
<td>Board</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>32</td>
<td>Pay</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>33</td>
<td>Accounting</td>
</tr>
<tr>
<td></td>
<td>10</td>
<td>Corporate Behavior</td>
<td>34</td>
<td>Business Ethics</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>35</td>
<td>Tax Transparency</td>
</tr>
</tbody>
</table>

Source: MSCI (2022, Exhibit 2, page 4).
## Table 2.9: Refinitiv materiality matrix

<table>
<thead>
<tr>
<th>Pillar</th>
<th>#</th>
<th>Theme</th>
<th>Metrics</th>
<th>#</th>
<th>Indicator</th>
</tr>
</thead>
<tbody>
<tr>
<td>Environment</td>
<td>1</td>
<td>Emissions</td>
<td>28</td>
<td>1</td>
<td>Emissions</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>2</td>
<td>Waste</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>3</td>
<td>Biodiversity</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>4</td>
<td>Environmental Management Systems</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>Innovation</td>
<td>20</td>
<td>5</td>
<td>Product Innovation</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>6</td>
<td>Green Revenues, Green R&amp;D and Green CapEx</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>Resource Use</td>
<td>20</td>
<td>7</td>
<td>Water</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>8</td>
<td>Energy</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>9</td>
<td>Sustainable Packaging</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>10</td>
<td>Environmental Supply Chain</td>
</tr>
<tr>
<td>Social</td>
<td>4</td>
<td>Community</td>
<td>14</td>
<td>11</td>
<td>Community</td>
</tr>
<tr>
<td></td>
<td>5</td>
<td>Human Rights</td>
<td>8</td>
<td>12</td>
<td>Human Rights</td>
</tr>
<tr>
<td></td>
<td>6</td>
<td>Product Responsibility</td>
<td>10</td>
<td>13</td>
<td>Responsible Marketing</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>14</td>
<td>Product Quality</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>15</td>
<td>Data privacy</td>
</tr>
<tr>
<td></td>
<td>7</td>
<td>Workforce</td>
<td>30</td>
<td>16</td>
<td>Diversity &amp; Inclusion</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>17</td>
<td>Career Development &amp; Training</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>18</td>
<td>Working Conditions</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>19</td>
<td>Health &amp; Safety</td>
</tr>
<tr>
<td>Governance</td>
<td>8</td>
<td>CSR Strategy</td>
<td>9</td>
<td>20</td>
<td>CSR Strategy</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>21</td>
<td>ESG Reporting &amp; Transparency</td>
</tr>
<tr>
<td></td>
<td>9</td>
<td>Management</td>
<td>35</td>
<td>22</td>
<td>Structure (independence, diversity, committees)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>23</td>
<td>Compensation</td>
</tr>
<tr>
<td></td>
<td>10</td>
<td>Shareholders</td>
<td>12</td>
<td>24</td>
<td>Shareholder Rights</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>25</td>
<td>Takeover Defenses</td>
</tr>
</tbody>
</table>

Source: Refinitiv (2022, page 10).

- FTSE Russell rates about 7,200 securities. They use more than 300 indicators and 14 themes: biodiversity, climate change, pollution and resources, supply chain and water security for the E pillar; customer responsibility, health and safety, human rights and community, labor standards and supply chain for the S pillar; anti-corruption, corporate governance, risk management and tax transparency for the G pillar. Each theme contains 10 to 35 indicators, and an average of 125 indicators are applied per company.

- Moody’s V.E rates more than 5,000 companies. They consider six pillars (corporate governance, business behavior, environment, human rights, human resources, community involvement) and 38 ESG indicators.\(^{28}\)

\(^{28}\)Moody’s has also developed a methodology for assessing ESG risks in credit analysis based on 15 themes: carbon transition, physical climate risks, water management, waste & pollution, natural capital for the E pillar; customer relations, human capital, demographic & societal trends, health & safety, responsible production for the S pillar; financial strategy & risk management, management credibility & track record, organizational structure, compliance & reporting, board structure & procedures for the G pillars.
Chapter 2. ESG Scoring

- **MSCI (2022)** rates 10 000 companies (14 000 issuers including subsidiaries) and 680 000 securities globally. Using 1000+ data points, they consider two families of metrics: 80 exposure metrics (how exposed is the company to each material issue?) and 250+ management metrics (how is the company managing each material issue?). These metrics are then combined into 35 key issues selected annually for each industry. These key metrics are reported in Table 2.8 and are combined to build 10 main themes.

- **Refinitiv (2022)** rates 12 000 public and private companies. They consider 10 themes: resource use, emissions and innovation for the E pillar; workforce, human rights, community and product responsibility for the S pillar; management, shareholders and responsibility (CSR) strategy for the G pillar. These themes are built using 186 metrics and 630+ data points. Table 2.9 shows the materiality matrix of themes, indicators and the number of metrics per theme.

- **S&P Dow Jones Indices** uses between 16 to 27 criteria scores, a questionnaire-based analysis process with 80-120 industry-specific questions and 1 000 data points.

- **Sustainalytics** rates more than 16 300 companies. They consider 20 material ESG issues, based on 350+ indicators.

**Remark 12** Contrary to sovereign issuers, raw data for corporate issuers are more difficult to find, because they are not in open source data or they can only be manually collected (e.g., annual reporting). The ESG Data Cartography, which has been developed by the Louis Bachelier Institute, proposes a comprehensive list of ESG data with 140+ data sources. The user can filter the databases by accessibility (free, open source, partially free and proprietary).

**Exercise 1** Berg et al. (2022) consider a common taxonomy based on 64 indicators to compare the different ESG rating providers: access to basic services; access to healthcare; animal welfare; anti-competitive practices; audit; biodiversity; board; board diversity; business ethics; chairperson-CEO separation; child labor; climate risk management; clinical trials; collective bargaining; community & society; corporate governance; corruption; customer relationship; diversity; ESG incentives; electromagnetic fields; employee development; employee turnover; energy; environmental fines; environmental management system; environmental policy; environmental reporting; financial inclusion; forests; GHG emissions; GHG policies; GMOs; Global Compact membership; green buildings; green products; HIV programs; hazardous waste; health & safety; human rights; indigenous rights; labor practices; lobbying; non-GHG air emissions; ozone-depleting gases; packaging; philanthropy; privacy & IT; product safety; public health; remuneration; reporting quality; resource efficiency; responsible marketing; shareholders; site closure; supply chain; sustainable finance; systemic risk; taxes; toxic spills; unions; waste; water. For each pillar, give the list of indicators that fall in the category. We consider a very basic ESG classification matrix with 12 themes:

<table>
<thead>
<tr>
<th>E</th>
<th>S</th>
<th>G</th>
</tr>
</thead>
<tbody>
<tr>
<td>Global warming</td>
<td>Health</td>
<td>Board</td>
</tr>
<tr>
<td>Green opportunities</td>
<td>Human rights</td>
<td>Corporate ethics</td>
</tr>
<tr>
<td>Natural resource</td>
<td>Workforce</td>
<td>CSR strategy</td>
</tr>
<tr>
<td>Transition risk</td>
<td>Social responsibility</td>
<td>Shareholder</td>
</tr>
</tbody>
</table>

For each indicator, associate the right ESG theme.

---


30 There may be no or several valid answers.
The race for alternative data

Alternative data corresponds to data that is not available through traditional channels (corporate publications, sustainable reporting, etc.). It includes non-structured data such as images or textual contents. The case of ESG ratings mainly concerns three types of data:

- Internet traffic, browsing activity, web scraping, product reviews, social media and sentiment data;
- Satellite imagery, geotracking data, sensor data\textsuperscript{31};
- Supply-chain data;

\textit{Brière et al.} (2022) discuss several uses of alternative data sets. The most famous application is the tracking and measurement of ESG controversies. A controversy risk occurs when allegations concerning a company could lead to reputational risk\textsuperscript{32} and financial losses. Everybody knows the famous quotes of Warren Buffet about building and destroying a reputation:

"It takes 20 years to build a reputation and five minutes to ruin it. If you think about that, you’ll do things differently. […] We can afford to lose money — even a lot of money. But we can’t afford to lose reputation — even a shred of reputation. […] Should you find yourself in a chronically leaking boat, energy devoted to changing vessels is likely to be more productive than energy devoted to patching leaks. […] Lose money for the firm, and I will be understanding. Lose a shred of reputation for the firm, and I will be ruthless."

The allegations can be reported by media, NGOs, social networks and stakeholders. Data providers generally use text mining and natural language processing (NLP) to analyze an enormous amount of information, detect controversial events and measure the severity of the reputational risk. For example, \textit{Refinitiv} (2022) completes the traditional ESG score with a controversy score for the 10 ESG themes presented in Table 2.9 on page 63. This score is updated on a weekly basis. The ESG controversies score is calculated based on 23 ESG controversy topics:

- Community: (1) anti-competition controversy, (2) business ethics controversies, (3) intellectual property controversies, (4) critical countries controversies, (5) public health controversies, (6) tax fraud controversies;
- Human rights: (7) child labour controversies, (8) human rights controversies;
- Management: (9) management compensation controversies count;
- Product responsibility: (10) consumer controversies, (11) customer health and safety controversies; (12) privacy controversies; (13) product access controversies; (14) responsible marketing controversies; (15) responsible R&D controversies;
- Resource use: (16) environmental controversies;
- Shareholders: (17) accounting controversies count, (18) insider dealings controversies, (19) shareholder rights controversies;

\textsuperscript{31}E.g., temperature, humidity, pressure, chemical levels.
\textsuperscript{32}Some famous examples are the \textit{Mexico oil spill} (BP, 2010), \textit{dieselgate} affair (Volkswagen, 2015), the gender pay gap (BBC, 2017), the Cambridge Analytica scandal (Facebook, 2018), the opioid epidemic (Purdue Pharma, 2019), the Ehpad scandal (Orpea, 2021), the Pegasus software (NSO, 2021), the greenwashing (DWS, 2022), etc.
Chapter 2. ESG Scoring

- Workforce: (20) diversity and opportunity controversies; (21) employee health and safety controversies; (22) wages or working conditions controversies; (23) strikes.

One of the most famous controversy data providers is the Swiss company RepRisk (https://www.reprisk.com), which was created in Zurich in 1998. They are specialized in ESG data science and machine learning. In November 2021, they published their comprehensive methodology (RepRisk, 2022) and Jupyter Notebooks. To identify and classify ESG risks consistent with how key international standards and norms define ESG, they consider a 3-step process:

1. Daily, they collect 500,000+ documents from 100,000+ sources in 23 languages;

2. These documents are scraped from online sources and fed to machine learning (ML) applications, which predict relevant and unique ESG risk incidents. Results are sent to the ML reducer, in particular, irrelevant results are discarded and predictions fed to the multilingual queue;

3. Then, documents are sorted in priority order. A team of 150+ human analysts confirm and correct ML predictions, assess severity, reach, and novelty, and write risk incident summaries; Final results are incorporated into RepRisk databases.

**Exercise 2** RepRisk (2022) uses 73 controversial topics: abusive/illegal fishing; access to products and services; agricultural commodity speculation; airborne pollutants; alcohol; animal transportation; arctic drilling; asbestos; automatic and semi-automatic weapons; biological weapons; chemical weapons; cluster munitions; coal-fired power plants; conflict minerals; coral reefs; cyberattack; deep sea drilling; depleted uranium munitions; diamonds; drones; economic impact; endangered species; energy management; epidemics/pandemics; forest burning; frocking; fur and exotic animal skins; gambling; gender inequality; genetically modified organisms (GMOs); genocide/ethnic cleansing; greenhouse gas (GHG) emissions; health impact; high conservation value forests; human trafficking; hydropower (dams); illegal logging; indigenous people; involuntary resettlement; land ecosystems; land grabbing; land mines; lobbying; marijuana/cannabis; marine/coastal ecosystems; migrant labor; monocultures; mountaintop removal mining; negligence; nuclear power; nuclear weapons; offshore drilling; oil sands; opioids; palm oil; plastics; pornography; predatory lending; privacy violations; protected areas; racism/racial inequality; rare earths; salaries and benefits; sand mining and dredging; seabed mining; security services; ship breaking and scrapping; soy; tax havens; tobacco; wastewaters management; water management; water scarcity. For each topic, associate the right ESG pillar.

Besides controversy risk, text mining and NLP techniques became recently an essential ML tool for different ESG applications. For example, they are more and more used for assessing company disclosures and verifying their credibility. Friederich et al. (2021) use the language model BERT to automatically identify disclosures of climate-related risks from corporates’ annual reports. In a similar way, Bingler et al. (2022) analyse climate risk disclosures along the TCFD categories and conclude that “the firms’ TCFD support is mostly cheap talk and that firms cherry-pick to report primarily non-material climate risk information”. Always using the same machine learning model

---

33 These include government agencies, news sites, newsletters, NGOs, print media, regulators, research firms, social media blogs, think tanks and twitter messages.

34 As of July 2022, the RepRisk dataset includes more than 205,000 companies that are associated with risk incidents. Of these 205,000 companies, approximately 7% are listed companies and 93% are non-listed companies (RepRisk, 2022, page 5).

35 Bidirectional Encoder Representations from Transformers (BERT) is a transformer-based machine learning technique for NLP pre-training developed by Google.
BERT, Köbel et al. (2022) consider the impact of climate risk disclosures on the CDS market and find that disclosing transition risks increases CDS spreads, which is not the case for physical risks.

Figure 2.8: Geolocation of world power plants by energy source

Another application of alternative data is the estimation of physical risk exposures. They correspond to the potential financial losses that companies can suffer, and includes droughts, floods, storms, etc. This risk is more difficult to quantify, and its evaluation requires multidisciplinary methodologies: climate modeling, physical asset geolocation, financial loss estimation, etc. In this case, asset tracking is really the crux of physical risk modeling. An example of spatial data is provided in Figure 2.8. This type of geolocalized data is extensively used by Le Guenedal et al. (2021, 2022) when developing a fully integrated methodology to measure cyclone-related physical risk. Until now, most of the models have been developed for countries and regions (Burke et al., 2021)(Burke et al., 2021). When dealing with corporate ESG, data providers generally use input-output matrices in order to compute the risk exposure or contribution of each firm. It is for example the case for biodiversity risk. Nevertheless, we have recently observed some initiatives to provide geospatial data and asset tracking directly at the company level. Even if these solutions are not yet mature, they are very promising.

Remark 13 Apart from controversies and physical risk, we also notice a third application of alternative data, which consists in building more reactive or real-time ESG scores. Ben Dor et al. (2022) propose to monitor planned sustainability-related corporate activities based on firms’ actions, rather than relying solely on their announcements. For that, they use job postings and NLP to identify ESG-related openings and ESG-related activities of firms. This technique can be used to understand the dynamics of sustainability within a firm.

36You can visit the website of the French technology company Kayrros (https://www.kayrros.com), which received the Financial Times ‘Tech Champions’ award for its innovation in the IT & Software sector. Kayrros uses satellite observation and AI to analyse trends in emissions and deforestation.
"This graph illustrates the ESG rating divergence. The horizontal axis indicates the value of the Sustainalytics rating as a benchmark for each firm (n = 924). Rating values by the other five raters are plotted on the vertical axis in different colors. For each rater, the distribution of values has been normalized to zero mean and unit variance. The Sustainalytics rating has discrete values that show up visually as vertical lines where several companies have the same rating value."

The divergence of corporate ESG ratings

Corporate ESG data are very different than sovereign ESG data in terms of standardization. Therefore, we must expect more discrepancies in ESG ratings. In Figure 2.9, we have reported one of the most famous illustrations about this rating disagreement extracted from the pioneering research of Berg et al. (2022). These authors investigate the divergence of ESG ratings from six prominent rating agencies: KLD, Moody’s ESG, MSCI, Refinitiv, S&P Global and Sustainalytics. Using the ESG metrics of these data providers, they reconstruct synthetic ratings based on a common taxonomy of 64 indicators. They identify three sources of divergence:

1. **Measurement** divergence refers to situation where rating agencies measure the same indicator using different ESG metrics;

2. **Scope** divergence refers to situation where ratings are based on different set of ESG indicators;

Source: Berg et al. (2022).
3. **Weight divergence** emerges when rating agencies take different views on the relative importance of ESG indicators.

They find that measurement contributes to 56% of the divergence, scope 38% and weight 6%.

Since this publication, the standardization issue of data and methodologies has been an ongoing discussion among practitioners and academics. For instance, Billio et al. (2021) analyze ESG ratings and indexes agreement and find that “it is extremely difficult to measure the ability of a fund manager if financial performances are strongly conditioned by the chosen ESG benchmark” and “disagreement in the scores provided by the rating agencies disperses the effect of preferences of ESG investors on asset prices”. In Table 2.10, we report their rank correlation matrix. On average, they obtain a mean correlation of 58% for corporate ESG ratings vs. 85% for sovereign ESG scores (Gratcheva et al., 2020).

<table>
<thead>
<tr>
<th></th>
<th>MSCI</th>
<th>Refinitiv</th>
<th>S&amp;P Global</th>
</tr>
</thead>
<tbody>
<tr>
<td>MSCI</td>
<td>100%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Refinitiv</td>
<td>43%</td>
<td>100%</td>
<td></td>
</tr>
<tr>
<td>S&amp;P Global</td>
<td>45%</td>
<td>69%</td>
<td>100%</td>
</tr>
<tr>
<td>Sustainalytics</td>
<td>53%</td>
<td>64%</td>
<td>69%</td>
</tr>
</tbody>
</table>

Source: Billio et al. (2021, Table 3, page 1432).

### 2.2 Scoring system

A scoring model is a mathematical model that forms the basis for risk stratification. For instance, credit scoring refers to statistical models to measure the creditworthiness of a company or a person (Roncalli, 2020a). In particular, the Altman Z score is certainly the most famous score for predicting the bankruptcy of commercial firms (Altman, 1968). Nevertheless, we can find scoring models in many fields. Thus, anti-money laundering (AML) scoring is a rating model to assess the risk profile of clients (Chen et al., 2018). The objective of trauma and field triage scoring systems is to predict injury severity or estimate the prognosis of trauma patients (Senkowski and McKenney, 1999). The Apgar score evaluates the physical condition of newborn infants shortly after delivery (Finster et al., 2005). In the case of medicine, we find many scoring systems: ACR score (rheumatoid arthritis symptoms), Alvarado score (appendicitis), Framingham and QRISK scores (cardiovascular risk), Geneva score (pulmonary embolism), etc.

At first sight, we may think that ESG scoring is an extension of credit scoring by using extra-financial data instead of financial data. And there are a lot of similarities between the two concepts: ESG ratings vs. credit ratings, ESG materiality vs. credit materiality, ESG risk vs. credit risk, etc. However, they are two different concepts from a mathematical viewpoint. Indeed, ESG scoring is an unsupervised approach to risk materiality while credit scoring is a supervised approach to risk materiality. In the case of credit, we would like to measure the one-year default probability.

---

**Unsupervised learning** is a branch of statistical learning, where test data does not include a response variable. It is opposed to supervised learning, whose goal is to predict the value of the response variable $Y$ given a set of explanatory variables $X$. In the case of unsupervised learning, we only know the $X$-values, because the $Y$-values do not exist or are not observed. Supervised and unsupervised learnings are also called “learning with/without a teacher” (Hastie et al., 2009). This metaphor means that we have access to the correct answer provided by the supervisor (or the teacher) in supervised learning. In the case of unsupervised learning, we have no feedback on the correct answer. For instance,
Therefore, credit scoring models are calibrated with a historical database of borrower default events. The response variable is then a binary variable, indicating 1 if the borrower has defaulted and 0 otherwise. In the case of ESG, we would like to measure the sustainability of issuers, but we face an endogenous puzzle since the ESG score is already the sustainability measure. The big issue with ESG scoring systems is then to define the response variable. Most of the time, the scoring model is not calibrated and is a simple rule-based method. This is why we generally consider ESG scoring as an unsupervised statistical approach. This has several drawbacks in terms of performance evaluation, score consistency and backtesting. Nevertheless, we will see that we can define some proxy for the response variable and use traditional statistical tools to assess the quality of ESG scores.

2.2.1 A primer on scoring theory

...
2.2.2 Tree-based scoring methods

Tree structure

To understand a tree-based scoring model, we first consider the one-level tree structure. Let \( X_1, \ldots, X_m \) be \( m \) features. These metrics are linearly combined to obtain a score:

\[
S = \sum_{j=1}^{m} \omega_j X_j
\]

where \( \omega_j \) is the weight of the \( j \)th metric. Generally, the weights are normalized such that \( \sum_{j=1}^{m} \omega_j = 1 \). This is the most simple scoring model. For instance, the original bankruptcy score of Altman (1968) was equal to:

\[
Z = 1.2 \cdot X_1 + 1.4 \cdot X_2 + 3.3 \cdot X_3 + 0.6 \cdot X_4 + 1.0 \cdot X_5
\]

where the variables \( X_j \) represent the following financial ratios:

<table>
<thead>
<tr>
<th>( X_j )</th>
<th>Ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>( X_1 )</td>
<td>Working capital / Total assets</td>
</tr>
<tr>
<td>( X_2 )</td>
<td>Retained earnings / Total assets</td>
</tr>
<tr>
<td>( X_3 )</td>
<td>Earnings before interest and tax / Total assets</td>
</tr>
<tr>
<td>( X_4 )</td>
<td>Market value of equity / Total liabilities</td>
</tr>
<tr>
<td>( X_5 )</td>
<td>Sales / Total assets</td>
</tr>
</tbody>
</table>

If we note \( Z_i \) the score of the firm \( i \), we can calculate the normalized score \( Z^*_i = (Z_i - m_z) / \sigma_z \) where \( m_z \) and \( \sigma_z \) are the mean and standard deviation of the observed scores. \( Z^*_i \) can then be compared to the quantile of the Gaussian distribution or the empirical distribution. A low value of \( Z^*_i \) (for instance \( Z^*_i < -2.5 \)) indicates that the firm has a high probability of default, while companies with high scores above (for instance \( Z^*_i > 3 \)) are not likely to go bankrupt.

We can extend the previous approach to a two-level tree structure. We first begin to compute intermediary scores:

\[
S^{(1)}_k = \sum_{j=1}^{m} \omega_{j,k}^{(1)} X_j
\]

Then we obtain a set of \( m^{(1)} \) intermediary scores \((k = 1, \ldots, m^{(1)})\), which are combined to obtain the final score:

\[
S := S^{(0)}_1 = \sum_{k=1}^{m^{(1)}} \omega_k^{(0)} S^{(1)}_k
\]

The exponents \((0)\) and \((1)\) indicate the level of the tree. An example of two-level tree structure is given in Figure 2.10. For the first level, we have:

\[
\begin{align*}
S^{(1)}_1 &= 0.5 \cdot X_1 + 0.25 \cdot X_2 + 0.25 \cdot X_3 \\
S^{(1)}_2 &= 0.5 \cdot X_4 + 0.5 \cdot X_5 \\
S^{(1)}_3 &= X_6
\end{align*}
\]

The final score is the average of the three intermediary scores:

\[
S = \frac{S^{(1)}_1 + S^{(1)}_2 + S^{(1)}_3}{3}
\]
Chapter 2. ESG Scoring

Figure 2.10: A two-level tree

- Level 1: \( \omega_{1,1}^{(1)} = 50\%; \omega_{2,1}^{(1)} = 25\%; \omega_{3,1}^{(1)} = 25\%; \omega_{4,2}^{(1)} = 25\%; \omega_{5,2}^{(1)} = 25\%; \omega_{6,3}^{(1)} = 100\%; \)
- Level 0: \( \omega_{1}^{(0)} = \omega_{2}^{(0)} = \omega_{3}^{(0)} = 33.33\%; \)

Figure 2.11: A two-level overlapping graph

- Level 1: \( \omega_{1,1}^{(1)} = 50\%; \omega_{2,1}^{(1)} = 25\%; \omega_{3,1}^{(1)} = 25\%; \omega_{4,2}^{(1)} = 25\%; \omega_{5,2}^{(1)} = 25\%; \omega_{6,3}^{(1)} = 50\%; \omega_{6,3}^{(1)} = 100\%; \)
- Level 0: \( \omega_{1}^{(0)} = \omega_{2}^{(0)} = \omega_{3}^{(0)} = 33.33\%; \)

This tree is a non-overlapping graph because each child node is related to a single parent node, otherwise it is an overlapping graph (but it is not a tree). For example, if we assume that the score \( S_2^{(1)} \) also depends on the metric \( X_3 \), we obtain the overlapping graph structure given in Figure 2.11.

In this case, the first level becomes:

\[
\begin{align*}
S_1^{(1)} &= 0.5 \cdot X_1 + 0.25 \cdot X_2 + 0.25 \cdot X_3 \\
S_2^{(1)} &= 0.25 \cdot X_3 + 0.25 \cdot X_4 + 0.5 \cdot X_5 \\
S_3^{(1)} &= X_6
\end{align*}
\]
A scoring tree is a special case of a tree data structure, which is defined as a collection of nodes that are organized in a hierarchical structure (see Figure 2.A). A tree is also a connected graph without any circuits\(^a\). Therefore, the terminology of trees derives from the graph theory. A node (or a vertex) is the basic unit that may contain data and links to other nodes. A connection between two nodes is called an edge. In a tree, edges are directed and are also called arcs or arrows. For instance, our example has 13 nodes \(V = (A, \ldots, M)\) and 12 edges \(E = \{\{K, H\}, \{L, J\}, \ldots, \{C, A\}, \{D, A\}\}\). Mathematically, the tree \(T\) is defined by the set \(V\) of nodes (or vertices) and the set \(E\) of edges: \(T = (V, E)\). In a tree, the first node is called the root node \((A)\). Any node within a tree can be viewed as a root of its own subtree. By definition, The subtree \(T_v(v)\) with \(v\) as its root is also a tree consisting of \(v\) and its descendants. \(T_v(v)\) is defined by \((V,v), E_v(v))\), where \(V_v(v)\) and \(E_v(v)\) are the sets of vertices and edges of the subgraph. Each edge (or directed path) has a child and a parent (or an internal node). For example, \(C\) is the parent node of \((H, I)\) and \(H\) is a child node of \(C\). Our example tree has then 6 parent nodes \(P = (A, B, C, D, H, J)\) and 12 children\(^b\). \(B\) has three children \((E, F, G)\) and \(B\) is a child of \(A\). Child nodes with the same parent are sibling nodes, while a leaf node (or external node) is a node without child nodes. In the example tree, \((B, C, D), (E, F, G), (H, I)\) are siblings. The leaf nodes are \((E, F, G, I, K, L, M)\). The degree of a node is its number of children. It is equal to 3 for \((A, B)\), 2 for \((C, J)\) and 1 for \((H, D)\) and 0 for the leaves. The degree of a tree is equal to the maximum degree of nodes. Our example tree has a degree 3. The level of a node refers to the distance between the node and the root. We deduce that the root node is at level 0. Children of the root are at level 1 \((B, C, D)\). Level 2 corresponds to the nodes \((E, F, G, H, I, J)\) and we have 3 nodes at level 3 \((K, L, M)\). The depth of a tree is the level of the deepest node. It is equal to 3 in our example tree.

---

\(^a\)We have the following properties:
- There is one and only one path between every pair of nodes in a tree;
- A tree with \(n\) nodes has exactly \(n - 1\) edges;
- A graph is a tree if and only if it is minimally connected;
- Any connected graph with \(n\) nodes and \(n - 1\) edges is a tree.

\(^b\)In a tree, the number of children is exactly equal to the number of edges.
The two-level tree structure can be extended to multi-level tree structures. Let $L$ be the number of levels. At level $\ell$, the value of the $k$th node is given by:

$$S_k^{(\ell)} = \sum_{j=1}^{m_{\ell+1}} \omega_{j,k}^{(\ell)} S_j^{(\ell+1)}$$

(2.1)

where $m_{\ell+1}$ is the number of scores at level $\ell + 1$, $S_j^{(\ell+1)}$ is the $j$th score at level $\ell + 1$ and $\omega_{j,k}^{(\ell)}$ is the weight of the $j$th score at level $\ell + 1$ for the $k$th score at level $\ell$. By construction, the scores at level $L$ are exactly equal to the features: $S_j^{(L)} = X_j$. We verify that the final score $S$ corresponds to the root score $S_1^{(0)}$. It can be computed by Algorithm 1. If we would like to target a specific level $\ell^*$, we replace the `for` statement $t = 1 : L$ by $t = 1 : L + 1 - \ell^*$.

**Algorithm 1** Recursive tree-based algorithm for computing the final score

Compute the final score $S_1^{(1)}$

**Input:** $L$ the number of levels, $(X_1, \ldots, X_m)$ the vector of the metrics and $\{\omega_{j,k}^{(\ell)}\}$ the weight tensor

**Initialize** $m_L = m$

for $j = 1 : m_L$ do

$S_j^{(L)} \leftarrow X_j$

end for

for $t = 1 : L$ do

\{Change the value of $L$ by $L - \ell^*$ if you target the level $\ell^*$\}

$\ell \leftarrow L - t$

for $k = 1 : m_{\ell}$ do

$S_k^{(\ell)} \leftarrow 0$

for $j = 1 : m_{\ell+1}$ do

$S_k^{(\ell)} \leftarrow S_k^{(\ell)} + \omega_{j,k}^{(\ell)} S_j^{(\ell+1)}$

end for

end for

end for

$S \leftarrow S_1^{(0)}$

return $S$

The multi-level tree structure is very popular for computing ESG scores. For instance, the final ESG score corresponds to level 0. It is the weighted average of the $E$, $S$, and $G$ scores, which form the first level. Each pillar depends on a number of ESG themes, which constitutes the second level. As we have seen previously, an ESG theme is made up of several indicators. These last ones are located at the third level of the scoring tree. The computation of indicators requires some ESG metrics. Therefore, an ESG scoring model has at least four levels. For example, we have reported in Figure 2.12 an example of a tree from the MSCI scoring model. Carbon emissions management and exposure are two metrics (level 4). They are combined to form the indicator carbon emissions (level 3). MSCI uses this indicator and four others to define the climate change theme (level 2). It is one of the four themes of the environmental pillar (level 1).
Score normalization

Why we need to normalize Let $\omega(\ell)$ be the $m(\ell+1) \times m(\ell)$ matrix, whose elements are $\omega_{j,k}^{(\ell)}$ for $j = 1, \ldots, m(\ell+1)$ and $k = 1, \ldots, m(\ell)$. We note $S^{(\ell)} = \begin{pmatrix} S_1^{(\ell)}, \ldots, S_{m(\ell)}^{(\ell)} \end{pmatrix}$ the vector of scores at the tree level $\ell$. We have:

$$S^{(\ell)} = \omega_{(\ell)}^T S^{(\ell+1)}$$

At level 1, we obtain $S_1^{(1)} = \omega_{(1)}^T S^{(2)}$. Since we have $S^{(2)} = \omega_{(2)}^T S^{(3)}$, we deduce that $S_1^{(1)} = \omega_{(1)}^T \omega_{(2)}^T S^{(3)}$. By iterating the previous equation and noting that $S^{(L)} = X$, the final score is equal to:

$$S = \omega^T X \quad (2.2)$$

where:

$$\omega = \omega_{(L-1)} \cdots \omega_{(1)} \omega_{(0)}$$

If we are interested in an intermediary score, we proceed in a similar way and we have:

$$S_k^{(\ell)} = e_k^T S^{(\ell)} = \omega_{\ell}^T X$$

where:

$$\omega = \omega_{(L-1)} \cdots \omega_{(1)} \omega_{(\ell)}$$

We conclude that all the scores are a weighted average of initial metrics.
Let us consider the scoring tree given in Figure 2.11. We have:

\[ \omega^{(1)} = \begin{bmatrix} 0.5 & 0 & 0 \\ 0.25 & 0 & 0 \\ 0.25 & 0.25 & 0 \\ 0 & 0.25 & 0 \\ 0 & 0.5 & 0 \\ 0 & 0 & 1 \end{bmatrix} \]

and:

\[ \omega^{(0)} = \frac{1}{3} \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix} \]

We deduce that:

\[ \omega = \omega^{(1)} \omega^{(0)} = \frac{1}{12} \begin{bmatrix} 2 \\ 1 \\ 2 \\ 2 \\ 4 \end{bmatrix} \]

The expression of the final score is:

\[ S = \frac{2X_1 + X_2 + 2X_3 + X_4 + 2X_5 + 4X_3}{12} \]

Let us assume that \( X \) follows a multivariate probability distribution \( F \). We deduce that \( S \) follows the univariate probability distribution \( G \) defined by:

\[ G(s) = \Pr \{ S \leq s \} = \Pr \{ \omega^T X \leq s \} = \int \cdots \int 1 \left\{ \sum_{j=1}^{m} \omega_j x_j \leq s \right\} dF (x) = \int \cdots \int 1 \left\{ \sum_{j=1}^{m} \omega_j x_j \leq s \right\} dF_1(x_1, \ldots, x_m) = \int \cdots \int 1 \left\{ \sum_{j=1}^{m} \omega_j x_j \leq s \right\} dC(F_1(x_1), \ldots, F_m(x_m)) \]

Therefore, the distribution \( G \) depends on the copula function \( C \) and the marginals \( (F_1, \ldots, F_m) \) of \( F \).

We first investigate the independent case. It follows that:

\[ G(s) = \int \cdots \int 1 \left\{ \sum_{j=1}^{m} \omega_j x_j \leq s \right\} \prod_{j=1}^{m} dF_j(x_j) \]
We deduce that $G$ is a convolution probability distribution. In some cases, it corresponds to a well-known probability distribution. For example, if $X_j \sim \mathcal{N}(\mu_j, \sigma_j^2)$, we have $\omega_j X_j \sim \mathcal{N}(\omega_j \mu_j, \omega_j^2 \sigma_j^2)$. We deduce that:

$$S \sim \mathcal{N}\left(\sum_{j=1}^{m} \omega_j \mu_j, \sum_{j=1}^{m} \omega_j^2 \sigma_j^2\right) \equiv \mathcal{N}\left(\omega^\top \mu, \omega^\top \Sigma \omega\right),$$

where $\mu = (\mu_1, \ldots, \mu_m)$ and $\Sigma = \text{diag}(\sigma_1^2, \ldots, \sigma_m^2)$. In Figure 2.13, we have reported the density function of the intermediary and final scores for the tree 2.10 when $X_j \sim \mathcal{N}(0, 1)$. The four scores $S_1^{(1)}, S_2^{(1)}, S_3^{(1)}$ and $S$ are Gaussian, centered at 0 with different standard deviations. We face here an issue because we cannot compare the different scores and it is impossible to have a homogeneous rule to assess whether a score is good or not.

Figure 2.13: Probability distribution of the scores (Tree 2.10)

Example 3 We assume that $X_1 \sim U[0, 1]$ and $X_2 \sim U[0, 1]$ are two independent random variables. We consider the score $S$ defined as:

$$S = \frac{X_1 + X_2}{2}$$

We have $S \in [0, 1]$. In Figure 2.14, we consider a geometric interpretation of the probability mass function $\Pr\{S \leq s\} = \Pr\{X_1 + X_2 \leq 2s\}$. We distinguish two cases. The first case (a) corresponds to $s \leq 0.5$. The probability mass corresponds then to the right triangle with vertices $(0, 0), (0, 2s)$ and $(2s, 0)$. It is equal to one-half the square, whose length is $2s$. The second case (b) corresponds to $0.5 \leq s \leq 1$. Here the probability mass is equal to the area of the polygon shape, whose vertices

---

40They are equal to 0.6124 for $S_1^{(1)}$, 0.7071 for $S_2^{(1)}$, 1 for $S_3^{(1)}$ and 0.4564 for $S$.
Figure 2.14: Geometric interpretation of the probability mass function (Example 3)

Case (a): $0 \leq s \leq 0.5$

Case (b): $0.5 \leq s \leq 1$

are $(0, 0), (1, 0), (1, 2s - 1), (2s - 1, 1)$ and $(0, 1)$. This is equivalent to computing the area of the unit square minus the right triangle with vertices $(1, 2s - 1), (1, 1)$ and $(2s - 1, 1)$. We notice that the area of the right triangle is equal to one-half the square, whose length is $2 - 2s$. We deduce that:

$$\Pr \{S \leq s\} = \begin{cases} \frac{1}{2} (2s)^2 & \text{if } 0 \leq s \leq \frac{1}{2} \\ 1 - \frac{1}{2} (2 - 2s)^2 & \text{if } \frac{1}{2} \leq s \leq 1 \end{cases}$$

Finally, we obtain:

$$G(s) = \begin{cases} 2s^2 & \text{if } 0 \leq s \leq \frac{1}{2} \\ -1 + 4s - 2s^2 & \text{if } \frac{1}{2} \leq s \leq 1 \end{cases}$$

The density function is then:

$$g(s) = \begin{cases} 4s & \text{if } 0 \leq s \leq \frac{1}{2} \\ 4 - 4s & \text{if } \frac{1}{2} \leq s \leq 1 \end{cases}$$

The previous results can be extended to the case $m > 2$. We can show that the score follows the Bates distribution\[^{41}\]:

$$S = \frac{X_1 + X_2 + \cdots + X_m}{m} \sim Bates(m)$$

In Figures 2.15 and 2.16, we report the density and distribution functions of the score for several values of $m$. We verify that the shape of the score depends on the number $m$ of features. In particular, we observe that the score tends to the Dirac distribution $\delta(x - 1/2)$.

Let us now investigate the dependent case. If we assume that $X \sim \mathcal{N} (\mu, \Sigma)$, the score $S = \omega^T X$ is normally distributed: $S \sim \mathcal{N}(\omega^T \mu, \omega^T \Sigma \omega)$. We consider that $\mu_j = 0$, $\sigma_j = 1$ and $\rho_{j,k} = \rho$ for $j \neq k$. Since the covariance matrix is the constant correlation matrix $\mathbb{C}_m(\rho)$, we deduce that

\[^{41}\text{See Exercise 2.4.1 on page 124.}\]
Figure 2.15: Probability density function of $S$ (uniform distribution)

Figure 2.16: Cumulative distribution function of $S$ (uniform distribution)
\[ \mathbb{E}[S] = 0 \text{ and } \]  

\[
\text{var}(S) = \omega^\top \mathbf{C}_m(\rho) \omega = \sum_{j=1}^{m} \sum_{k=1}^{m} \omega_j \omega_k \rho_{j,k} + \left( \sum_{j=1}^{m} \omega_j^2 \rho - \sum_{j=1}^{m} \omega_j^2 \right) = \rho \sum_{j=1}^{m} \sum_{k=1}^{m} \omega_j \omega_k + (1 - \rho) \sum_{j=1}^{m} \omega_j^2 = \rho S^2(w) + (1 - \rho) \mathcal{H}(\omega)
\]

where \( S(w) = \sum_{j=1}^{m} \omega_j \) is the sum index and \( \mathcal{H}(\omega) = \sum_{j=1}^{m} \omega_j^2 \) is the Herfindahl index. Generally, the weights are normalized and we obtain \( S \sim \mathcal{N}(0, \sigma^2_S) \) where:

\[ \sigma_S = \sqrt{\rho + (1 - \rho) \mathcal{H}(\omega)} \]

Since \( 0 \leq \mathcal{H}(\omega) \leq 1 \), \( \sigma_S \in [\sqrt{\rho}, 1] \). When the weights are equal \( (\omega_j = 1/m) \), the previous formula reduces to:

\[ \sigma_S = \sqrt{\rho + \frac{(1 - \rho)}{m}} \]

Let us build the confidence interval of the score at the confidence level \( \alpha \). We have \( \Pr\{S \in [S^-(m, \alpha), S^+(m, \alpha)]\} = \alpha \). Since the expectation of the score is equal to zero, we consider an interval centered at 0. We deduce that:

\[ S^+(m, \alpha) = \Phi^{-1}\left(\frac{1 + \alpha}{2}\right) \sqrt{\rho + \frac{(1 - \rho)}{m}} \]

and \( S^-(m, \alpha) = -S^+(m, \alpha) \).

In Figure 2.17, we illustrate the shrinkage issue of the score when \( \alpha \) is set to 99.75%. At this confidence level, a standard normal random variable lies between \(-3\) and \(+3\). This is the range that we have in mind when we build a \( z \)-score. We observe that the shrinkage begins when the score is made up of three features and a correlation lower than 80%. The shrinkage issue increases with the number of features. Let us consider for example an ESG score that depends on \( 3 \) features and a correlation lower than \( 20\% \). While the range of the features is between \(-3\) and \(+3\), the aggregate ESG score lies between \(-1.5\) and \(+1.5\), meaning that the support of the score has been divided by a factor of two!

**How to normalize?** The previous analysis implies that we must normalize the raw data and the scores at the different levels such that they follow the same probability distribution \( \mathbf{F}_S \). Equation (2.1) is no longer valid and we deduce that the node values of the multi-level tree structure are equal to:

\[ \mathbf{S}_k^{(\ell)} = \varphi \left( \sum_{j=1}^{m} \omega_{j,k} \mathbf{S}_j^{(\ell+1)} \right) \]

where \( \varphi(s) \) is the normalization function. We also have \( \mathbf{S}_j^{(L)} = \varphi(X_j) \).

Let \( X \) be a variable to normalize and \( \{x_1, \ldots, x_n\} \) a sample of \( n \) observations. In practice, there are three main approaches:

---

\[ ^{42}\text{We note } S(w) = \sum_{j=1}^{m} \omega_j. \text{ We deduce that } \left( \sum_{j=1}^{m} \omega_j \right)^2 = \sum_{j=1}^{m} \sum_{k=1}^{m} \omega_j \omega_k = S^2(w). \]

\[ ^{43}\text{We have } \mathcal{H}(\omega) = \sum_{j=1}^{m} (1/m)^2 = 1/m. \]
Chapter 2. ESG Scoring

Figure 2.17: Upper and lower bounds of the aggregate score when $\alpha = 99.75\%$

1. The first one is the $m$-score (or min-max) normalization:

$$m_i = \frac{x_i - x^-}{x^+ - x^-}$$

where $x^- = \min x_i$ and $x^+ = \max x_i$. This is the most naive approach to obtain a 0/1 normalization.

2. The second approach is the $q$-score (or quantile) normalization:

$$q_i = H(x_i)$$

where $H$ is the distribution function of $X$. When the distribution of $X$ is unknown, we replace $H$ by the empirical distribution $\hat{H}$: $q_i = \hat{H}(x_i)$. In both cases, we obtain a 0/1 normalization.

3. The third method is the famous $z$-score normalization:

$$z_i = \frac{x_i - \mu}{\sigma}$$

where $\mu$ and $\sigma$ are the mathematical expectation and standard deviation of $X$. Again, when the distribution of $X$ is unknown, we use the empirical mean and standard deviation of the sample:

$$z_i = \frac{x_i - \hat{\mu}}{\hat{\sigma}}$$

By construction, we have $z_i \in (-\infty, \infty)$. Nevertheless, we have seen that $\Pr \{ -3 \leq N(0,1) \leq 3 \} \approx 99.75\%$. Generally, we consider that the $z$-score method produces a $-3/ + 3$ normalization.

Handbook of Sustainable Finance
Among the three approaches, only the second approach satisfies the consistency property. Indeed, if \( X \sim H \) and is continuous, we know that \( Y = H(X) \) is a uniform random variable\(^{44} \). \( Y = H(X) \) defines the probability integral transform, which plays an important role in statistics and probability. The min-max approach is consistent only if \( X \sim U_{[x-,x+]} \), whereas the z-score normalization is consistent if the original data are normally distributed.

**Box 2.3: Computing the empirical distribution \( \hat{H} \)**

Let \( \{x_1, x_2, \ldots, x_n\} \) be the sample. We have:

\[
q_i = \hat{H}(x_i) = \Pr \{ X \leq x_i \} = \frac{\# \{ x_j \leq x_i \}}{n_q}
\]

We can use two normalization factors: \( n_q = n \) or \( n_q = n + 1 \). For example, if \( n = 4 \), we have \( q_i \in \{0.25, 0.5, 0.75, 1\} \) if \( n_q = n \), and \( q_i \in \{0.2, 0.4, 0.6, 0.8\} \) if \( n_q = n + 1 \). The second solution is better because \( q_i \in [0,1] \). Therefore, we can transform \( q_i \) into a random variable \( Y \) with probability distribution \( G \) by considering the inverse probability integral transform:

\[
Y = G^{-1}(q_i) \sim G
\]

For example, we can transform a \( q \)-score into a \( z \)-score by considering the Gaussian quantile function:

\[
z = \Phi^{-1}(q)
\]

With the second solution, we are sure that \( z \notin (-\infty, \infty) \).

To obtain an \( a/b \) normalization, we consider the following property:

\[
U_{[a,b]} = a + (b - a)U_{[0,1]}
\]

Therefore, we apply the following transform to obtain the new score:

\[
q' = a + (b - a)q
\]

The \( q \)-score is distributed according to the uniform distribution. It has the advantage to be normalized between 0 and 1. However, it has the disadvantage to be a flat score, meaning that the extreme scores have the same probability to occur as the mean score. The \( z \)-score is distributed according to the Gaussian distribution. It has a bell-curve shape, meaning that the extreme scores have a lower probability to occur than the mean score. Therefore, it is interesting to combine the two properties to obtain a discriminant score between 0 and 1. This is done by considering the \( b \)-score using a Beta distribution \( B(\alpha, \beta) \). In this case, we have:

\[
b_i = B^{-1}(H(x_i) ; \alpha, \beta)
\]

\(^{44}\)We have \( Y \in [0,1] \) and:

\[
\Pr \{ Y \leq y \} = \Pr \{ H(X) \leq y \} = \Pr \{ X \leq H^{-1}(y) \} = H(H^{-1}(y)) = y
\]

We deduce that \( Y \sim U_{[0,1]} \).
When $\alpha = \beta$, this creates a symmetric score around 0.5. To obtain a left-skewed score (when having more best-in-class issuers than worst-in-class issuers), we use $\alpha > \beta$. The case $\alpha < \beta$ produces a right-skewed score (when having more worst-in-class issuers than best-in-class issuers). The standard values for parameters are $\alpha = \beta = 2$.

**Example 4** The data are normally distributed with mean $\mu = 5$ and standard deviation $\sigma = 2$. To map these data into a 0/1 score, we consider the following transform:

$$s := \varphi(x) = \mathcal{B}^{-1} \left( \Phi \left( \frac{x - 5}{2} \right); \alpha, \beta \right)$$

In Figure 2.18, we report the transform function $\varphi(x)$ and the final distribution for three sets of parameters $(\alpha, \beta)$.

**Remark 14** ESG data providers do not publish their statistical methodology for computing ESG scores\(^4\). It is then difficult to know which normalization approach is used. Nevertheless, they give the scale of the scores. Bloomberg, S&P Global and Sustainalytics use a range from 0 to 100, Refinitiv from 1 to 100, MSCI from 0 to 10, ISS ESG from 1 to 10, etc. Some asset managers use a scale between $-3$ and $+3$.

\(^4\)Only S&P Dow Jones Indices (2022, page 8) indicates that “the normalization is performed by a sigmoid-function on a standard $z$-score”:

$$S = \frac{2}{1 + e^{-z}} - 1 \in [-1, 1]$$

Handbook of Sustainable Finance
Example 5 We consider the raw data of 9 companies in Table 2.11. These companies belong to the same industry. The first variable measures the carbon intensity of scope 1 + 2 in 2020, while the second variable is the variation of carbon emissions between 2015 and 2020. We would like to create the score \( S \equiv 70\% \cdot X_1 + 30\% \cdot X_2 \).

Table 2.11: Raw data of 9 companies (carbon emissions and carbon momentum)

<table>
<thead>
<tr>
<th>Firm</th>
<th>Carbon intensity (in tCO(_2e)/$ mn)</th>
<th>Carbon momentum (in %)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>94.0</td>
<td>-3.0</td>
</tr>
<tr>
<td>2</td>
<td>38.6</td>
<td>-5.5</td>
</tr>
<tr>
<td>3</td>
<td>30.6</td>
<td>5.6</td>
</tr>
<tr>
<td>4</td>
<td>74.4</td>
<td>-1.3</td>
</tr>
<tr>
<td>5</td>
<td>97.1</td>
<td>-16.8</td>
</tr>
<tr>
<td>6</td>
<td>57.1</td>
<td>-3.5</td>
</tr>
<tr>
<td>7</td>
<td>132.4</td>
<td>8.5</td>
</tr>
<tr>
<td>8</td>
<td>92.5</td>
<td>-9.1</td>
</tr>
<tr>
<td>9</td>
<td>64.9</td>
<td>-4.6</td>
</tr>
</tbody>
</table>

To create the synthetic score, we must analyze the data. An ESG investor prefers to be exposed to low-carbon companies than to high-carbon companies. Similarly, he favors firms that have reduced their carbon emissions in the past. If we consider the raw variables as the two features, a high value of the score will indicate a worst-in-class company while a low value of the score will indicate a best-in-class company. If we prefer that high scores correspond to best-in-class scores, we need to take the opposite of these data. We consider the first choice. In Table 2.12, we report the computation of the score by using a \( q \)-score \( 0/100 \) normalization. For instance, company #7 has the highest carbon emission and then the highest score \( q_1 = 90 \). It is followed by company #5 which has a score of 80. We verify that the mean of \( q_1 \) is equal to \((0 + 100)/2\) and its standard deviation is approximately\(^{46}\) equal to \( \sqrt{(100 - 0)^2/12} \). For the carbon momentum, the best issuer is company #5 with a trend of \(-16.8\%\), and its \( q \)-score is equal to 10. We compute then the score \( s = 0.7 \cdot q_1 + 0.3 \cdot q_2 \). This indicates that the ESG investor is more sensitive to carbon intensity than carbon intensity. Said differently, he would like to build a score primarily based on the carbon intensity, but he would like to penalize companies that increase their carbon emissions. For the first firm, we obtain \( s = 0.7 \times 70 + 0.3 \times 60 = 67 \). We notice that the standard deviation of the variable \( s \) is equal to 20.60, which is lower than 27.39. Again, we have to normalize the variable \( s \) and we obtain the final score. We also report the rank \( R \) and we obtain the following ordering:

\[ \#2 \succ \#3 \succ \#6 \succ \#9 \succ \#8 \succ \#4 \succ \#5 \succ \#1 \succ \#7 \]

We deduce that the best-in-class and worst-in-class issuers are respectively companies #2 and #7. If we consider the \( z \)-score normalization, the results are given in Table 2.13. For example, \( z_1 \) and \( z_2 \) are equal to \((92.5 - 75.73)/31.95 = 0.525 \) and \((-9.10 + 3.30)/7.46 = -0.778 \) for company #8. We deduce that \( s = 0.7 \times 0.525 + 0.3 \times (-0.778) = 0.134 \). Again we observe that the variable \( s \) is not normalized since its standard deviation is not equal to 1. We deduce that \( S = (0.134 - 0.000)/0.759 = 0.177 \). Finally, we obtain the following ordering:

\[ \#2 \succ \#3 \succ \#6 \succ \#9 \succ \#5 \succ \#4 \succ \#8 \succ \#1 \succ \#7 \]

We conclude that the two approaches produce two different rankings.

Handbook of Sustainable Finance
Table 2.12: Computation of the score $\mathcal{S} = 70\% \cdot X_1 + 30\% \cdot X_2$ ($q$-score normalization)

<table>
<thead>
<tr>
<th>#</th>
<th>$X_1$</th>
<th>$q_1$</th>
<th>$X_2$</th>
<th>$q_2$</th>
<th>$s$</th>
<th>$\mathcal{S}$</th>
<th>$\mathcal{R}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>94.00</td>
<td>70.00</td>
<td>−3.00</td>
<td>60.00</td>
<td>67.00</td>
<td>80.00 8</td>
<td>8</td>
</tr>
<tr>
<td>2</td>
<td>38.60</td>
<td>20.00</td>
<td>−5.50</td>
<td>30.00</td>
<td>23.00</td>
<td>10.00 1</td>
<td>1</td>
</tr>
<tr>
<td>3</td>
<td>30.60</td>
<td>10.00</td>
<td>5.60</td>
<td>80.00</td>
<td>31.00</td>
<td>20.00 2</td>
<td>2</td>
</tr>
<tr>
<td>4</td>
<td>74.40</td>
<td>50.00</td>
<td>−1.30</td>
<td>70.00</td>
<td>56.00</td>
<td>60.00 6</td>
<td>6</td>
</tr>
<tr>
<td>5</td>
<td>97.10</td>
<td>80.00</td>
<td>−16.80</td>
<td>10.00</td>
<td>59.00</td>
<td>70.00 7</td>
<td>7</td>
</tr>
<tr>
<td>6</td>
<td>57.10</td>
<td>30.00</td>
<td>−3.50</td>
<td>50.00</td>
<td>36.00</td>
<td>30.00 3</td>
<td>3</td>
</tr>
<tr>
<td>7</td>
<td>132.40</td>
<td>90.00</td>
<td>8.50</td>
<td>90.00</td>
<td>90.00</td>
<td>90.00 9</td>
<td>9</td>
</tr>
<tr>
<td>8</td>
<td>92.50</td>
<td>60.00</td>
<td>−9.10</td>
<td>20.00</td>
<td>48.00</td>
<td>50.00 5</td>
<td>5</td>
</tr>
<tr>
<td>9</td>
<td>64.90</td>
<td>40.00</td>
<td>−4.60</td>
<td>40.00</td>
<td>40.00</td>
<td>40.00 4</td>
<td>4</td>
</tr>
<tr>
<td>Mean</td>
<td>75.73</td>
<td>50.00</td>
<td>−3.30</td>
<td>50.00</td>
<td>50.00</td>
<td>50.00 4</td>
<td>4</td>
</tr>
<tr>
<td>Std-dev.</td>
<td>31.95</td>
<td>27.39</td>
<td>7.46</td>
<td>27.39</td>
<td>20.60</td>
<td>27.39</td>
<td></td>
</tr>
</tbody>
</table>

Table 2.13: Computation of the score $\mathcal{S} = 70\% \cdot X_1 + 30\% \cdot X_2$ ($z$-score normalization)

<table>
<thead>
<tr>
<th>#</th>
<th>$X_1$</th>
<th>$z_1$</th>
<th>$X_2$</th>
<th>$z_2$</th>
<th>$s$</th>
<th>$\mathcal{S}$</th>
<th>$\mathcal{R}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>94.00</td>
<td>0.572</td>
<td>−3.00</td>
<td>0.040</td>
<td>0.412</td>
<td>0.543 8</td>
<td>8</td>
</tr>
<tr>
<td>2</td>
<td>38.60</td>
<td>−1.162</td>
<td>−5.50</td>
<td>−0.295</td>
<td>−0.902</td>
<td>−1.188 1</td>
<td>1</td>
</tr>
<tr>
<td>3</td>
<td>30.60</td>
<td>−1.413</td>
<td>5.60</td>
<td>1.193</td>
<td>−0.631</td>
<td>−0.831 2</td>
<td>2</td>
</tr>
<tr>
<td>4</td>
<td>74.40</td>
<td>−0.042</td>
<td>−1.30</td>
<td>0.268</td>
<td>0.051</td>
<td>0.067 6</td>
<td>6</td>
</tr>
<tr>
<td>5</td>
<td>97.10</td>
<td>0.669</td>
<td>−16.80</td>
<td>−1.810</td>
<td>−0.075</td>
<td>−0.099 5</td>
<td>5</td>
</tr>
<tr>
<td>6</td>
<td>57.10</td>
<td>−0.583</td>
<td>−3.50</td>
<td>−0.027</td>
<td>−0.416</td>
<td>−0.548 3</td>
<td>3</td>
</tr>
<tr>
<td>7</td>
<td>132.40</td>
<td>1.774</td>
<td>8.50</td>
<td>1.582</td>
<td>1.716</td>
<td>2.261 9</td>
<td>9</td>
</tr>
<tr>
<td>8</td>
<td>92.50</td>
<td>0.525</td>
<td>−9.10</td>
<td>−0.778</td>
<td>0.134</td>
<td>0.177 7</td>
<td>7</td>
</tr>
<tr>
<td>9</td>
<td>64.90</td>
<td>−0.339</td>
<td>−4.60</td>
<td>−0.174</td>
<td>−0.290</td>
<td>−0.382 4</td>
<td>4</td>
</tr>
<tr>
<td>Mean</td>
<td>75.73</td>
<td>0.000</td>
<td>−3.30</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000 0</td>
<td>0</td>
</tr>
<tr>
<td>Std-dev.</td>
<td>31.95</td>
<td>1.000</td>
<td>7.46</td>
<td>1.000</td>
<td>0.759</td>
<td>1.000</td>
<td></td>
</tr>
</tbody>
</table>

Table 2.14: Comparison of the different scoring methods

<table>
<thead>
<tr>
<th>#</th>
<th>$q$</th>
<th>$\mathcal{R}$</th>
<th>$z$</th>
<th>$\mathcal{R}$</th>
<th>$qz$</th>
<th>$\mathcal{R}$</th>
<th>$zq$</th>
<th>$\mathcal{R}$</th>
<th>$bz$</th>
<th>$\mathcal{R}$</th>
<th>$bz^*$</th>
<th>$\mathcal{R}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>80.00</td>
<td>8</td>
<td>0.54</td>
<td>8</td>
<td>76.27</td>
<td>8</td>
<td>0.84</td>
<td>8</td>
<td>0.66</td>
<td>8</td>
<td>0.81</td>
<td>8</td>
</tr>
<tr>
<td>2</td>
<td>10.00</td>
<td>1</td>
<td>−1.19</td>
<td>1</td>
<td>9.19</td>
<td>1</td>
<td>−1.28</td>
<td>1</td>
<td>0.20</td>
<td>1</td>
<td>0.30</td>
<td>1</td>
</tr>
<tr>
<td>3</td>
<td>20.00</td>
<td>2</td>
<td>−0.83</td>
<td>2</td>
<td>21.37</td>
<td>2</td>
<td>−0.84</td>
<td>2</td>
<td>0.29</td>
<td>2</td>
<td>0.38</td>
<td>2</td>
</tr>
<tr>
<td>4</td>
<td>60.00</td>
<td>6</td>
<td>0.07</td>
<td>6</td>
<td>54.13</td>
<td>5</td>
<td>0.25</td>
<td>6</td>
<td>0.52</td>
<td>6</td>
<td>0.70</td>
<td>6</td>
</tr>
<tr>
<td>5</td>
<td>70.00</td>
<td>7</td>
<td>−0.10</td>
<td>5</td>
<td>56.65</td>
<td>6</td>
<td>0.52</td>
<td>7</td>
<td>0.51</td>
<td>5</td>
<td>0.64</td>
<td>5</td>
</tr>
<tr>
<td>6</td>
<td>30.00</td>
<td>3</td>
<td>−0.55</td>
<td>3</td>
<td>24.42</td>
<td>3</td>
<td>−0.52</td>
<td>3</td>
<td>0.34</td>
<td>3</td>
<td>0.50</td>
<td>3</td>
</tr>
<tr>
<td>7</td>
<td>90.00</td>
<td>9</td>
<td>2.26</td>
<td>9</td>
<td>98.04</td>
<td>9</td>
<td>1.28</td>
<td>9</td>
<td>0.93</td>
<td>9</td>
<td>0.96</td>
<td>9</td>
</tr>
<tr>
<td>8</td>
<td>50.00</td>
<td>5</td>
<td>0.18</td>
<td>7</td>
<td>60.39</td>
<td>7</td>
<td>0.00</td>
<td>5</td>
<td>0.56</td>
<td>7</td>
<td>0.72</td>
<td>7</td>
</tr>
<tr>
<td>9</td>
<td>40.00</td>
<td>4</td>
<td>−0.38</td>
<td>4</td>
<td>30.96</td>
<td>4</td>
<td>−0.25</td>
<td>4</td>
<td>0.39</td>
<td>4</td>
<td>0.56</td>
<td>4</td>
</tr>
<tr>
<td>Mean</td>
<td>50.00</td>
<td>0.00</td>
<td>47.94</td>
<td>0.00</td>
<td>0.49</td>
<td>0.62</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Std-dev.</td>
<td>27.39</td>
<td>1.00</td>
<td>28.79</td>
<td>0.82</td>
<td>0.22</td>
<td>0.21</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
In Table 2.14, we compare the scores and the ranks obtained for different scoring schemes. Besides the \( q \)- and \( z \)-scores, we consider the following transforms:

- The \( qz \)-score is defined as:
  \[
  qz = c \cdot \Phi (z) \in [0, c]
  \]
  where \( c = 100 \) is the scaling factor.

- The \( zq \)-score is defined as:
  \[
  zq = \Phi^{-1} \left( \frac{q}{c} \right) \in [-3, 3]
  \]

- The \( bz \)-score is defined as:
  \[
  bz = \mathfrak{B}^{-1} (\Phi (z); \alpha, \beta) \in [0, 1]
  \]
  where \( \alpha = \beta = 2 \).

- The \( bz^* \)-score is a modification of the \( bz \)-score by using \( \alpha = 2.5 \) and \( \beta = 1.5 \).

We verify that the \( bz^* \)-score is left-skewed and the mean is above \( 1/2 \).

**Remark 15** Most ESG scoring systems are sector neutral, meaning that the normalization is done at the sector (or industry) level, not at the issuer universe level. ESG scores are then **relative** scores (with respect to the sector/industry), not **absolute** scores. This is the concept of best-in-class/worst-in-class issuers. A best-in-class company is then not a best-in-universe issuer. Let us consider the example where the score of corporate \( A \) is \( S_A = +2 \) and the score of corporate \( B \) is \( S_B = +1 \). We have:

- If \( A \) and \( B \) belong to the same sector, we have \( A \succ B \);
- If \( A \) and \( B \) belong to two different sectors, we may have \( A \succ B \) or \( B \succ A \).

The preference ordering \( \succ \) is then partial and not total.

**An example with the CEO pay ratio** The CEO pay ratio is calculated by dividing the CEO’s compensation by the pay of the median employee. It is one of the key metrics for the \( \mathbb{G} \) pillar. It has been imposed by the Dodd-Frank Act, which requires that publicly traded companies disclose:

1. the median total annual compensation of all employees other than the CEO;
2. the ratio of the CEO’s annual total compensation to that of the median employee;
3. the wage ratio of the CEO to the median employee.

According to the American Federation of Labor and Congress of Industrial Organizations (AFL-CIO, https://aflcio.org), the average S&P 500 company’s CEO-to-worker pay ratio was 324-to-1 in 2021. In Table 2.15, we have reported some data collected by this organization (\( P \) is the median worker pay (in \$) and \( R \) is the CEO pay ratio).

Computing the scores for the pay ratio is a real challenge, because the probability distribution of the pay ratio has both a high skew and a big kurtosis. To illustrate these issues, Figure 2.19 shows the histogram of the CEO pay ratios for all US public companies\footnote{Since we have only 9 observations, we observe a small difference between the true and the sample values.} for the fiscal year 2021. If we\footnote{We use the database *Fiscal 2021 CEO Pay Ratios* by Mark Siciliano, which can be downloaded at the University of Alabama: https://ir.ua.edu/handle/123456789/8639.}
Table 2.15: Examples of CEO pay ratio (June 2021)

<table>
<thead>
<tr>
<th>Company name</th>
<th>P</th>
<th>R</th>
<th>Company name</th>
<th>P</th>
<th>R</th>
</tr>
</thead>
<tbody>
<tr>
<td>Abercrombie &amp; Fitch</td>
<td>1954</td>
<td>4,293</td>
<td>Netflix</td>
<td>20293</td>
<td>190</td>
</tr>
<tr>
<td>McDonald’s</td>
<td>9,291</td>
<td>1,939</td>
<td>BlackRock</td>
<td>133,644</td>
<td>182</td>
</tr>
<tr>
<td>Coca-Cola</td>
<td>11,285</td>
<td>1,657</td>
<td>Pfizer</td>
<td>98,972</td>
<td>181</td>
</tr>
<tr>
<td>Gap</td>
<td>6,177</td>
<td>1,558</td>
<td>Goldman Sachs</td>
<td>138,854</td>
<td>178</td>
</tr>
<tr>
<td>Alphabet</td>
<td>258,708</td>
<td>1,085</td>
<td>MSCI</td>
<td>55,857</td>
<td>165</td>
</tr>
<tr>
<td>Walmart</td>
<td>22,484</td>
<td>983</td>
<td>Verisk Analytics</td>
<td>77,055</td>
<td>117</td>
</tr>
<tr>
<td>Estee Lauder</td>
<td>30,733</td>
<td>697</td>
<td>Facebook</td>
<td>247,883</td>
<td>94</td>
</tr>
<tr>
<td>Ralph Lauren</td>
<td>21,358</td>
<td>570</td>
<td>Invesco</td>
<td>125,282</td>
<td>92</td>
</tr>
<tr>
<td>NIKE</td>
<td>25,386</td>
<td>550</td>
<td>Boeing</td>
<td>158,869</td>
<td>90</td>
</tr>
<tr>
<td>Citigroup</td>
<td>52,988</td>
<td>482</td>
<td>Citrix Systems</td>
<td>181,769</td>
<td>80</td>
</tr>
<tr>
<td>PepsiCo</td>
<td>45,896</td>
<td>368</td>
<td>Harley-Davidson</td>
<td>187,157</td>
<td>59</td>
</tr>
<tr>
<td>Microsoft</td>
<td>172,512</td>
<td>249</td>
<td>Amazon.com</td>
<td>28,848</td>
<td>58</td>
</tr>
<tr>
<td>Apple</td>
<td>57,596</td>
<td>201</td>
<td>Berkshire Hathaway</td>
<td>65,740</td>
<td>6</td>
</tr>
</tbody>
</table>

Source: https://aflcio.org (June 2021)

Figure 2.19: Histogram of the CEO pay ratio
compute the $z$-score directly from the pay ratio, we obtain the blue histogram in Figure 2.20. This $z$-score has a mean around 0 and a standard deviation of 1, but we have $z \in (-0.338, 3.869)$. If we do the same exercise with the logarithm of the CEO pay ratio, we obtain the red histogram. In this case, we have $z \in (-3.561, 4.545)$. This is better, but it is not perfect. This example demonstrates that we must conduct a deep analysis of each data before applying a blind scoring approach. Most ESG data are skewed with fat tails, some of them are binary, others take discrete values, etc. In this context, data analysis is essential to choose the right normalization and scoring transform.

**Exercise 6** The database of the CEO pay ratios for all US public companies contains several sector/industry variables. Compute the $z$-score of the CEO pay ratio and its logarithm at the sector level. Identify the most problematic sectors. Same question if we consider the industry level.
2.2.3 Other statistical methods

2.2.4 Performance evaluation criteria

This section is dedicated to the performance assessment of a score. Backtesting an ESG score is relatively close to backtesting a credit score. Even if the tree-based scoring model is an unsupervised learning approach, we have seen that it is possible to build supervised models by using a control variable. The response function can be exogenous such as the controversy index \( C(t) \) or the controversy indicator \( I(t) = 1 \{ C(t) > 0 \} \). It can also be endogenous by considering control variables based on the score \( S(t+\delta) \) in the future. Examples are the best-in-class risk indicator \( G(t, \delta) = 1 \{ S(t+\delta) \geq s^* \} \) or the worst-in-class risk indicator \( B(t, \delta) = 1 \{ S(t+\delta) \leq s^* \} \). They are noted \( G \) and \( B \) by analogy with the risk theory that distinguishes good and bad risk. For instance, credit scoring models are mainly based on bad risk detection. This is also the same thing in the case of responsible investing. Nevertheless, we might also want to have a statistical model, whose main objective is to select the good issuers. In the case of the ESG momentum strategy, the response variable depends on the improvement of the ESG score. It can be defined as \(^{46}\) \( \mathcal{M}(t, \delta) = 1 \{ S(t+\delta) - S(t) \geq \Delta^*_s \} \).

Remark 16 In this section, the score \( S \) is not necessarily the final ESG score. It corresponds to any score or screening rule derived from the ESG scoring model. For instance, it may corresponds to a selection score, an exclusion score, etc.

We notice that most control variables are binary. Therefore, we can use the classical tool of credit scoring and follow Roncalli (2020a, Chapter 15) to assess the performance of scoring models. In the first paragraph, we use information theory to know if the scoring system is informative or not. The second paragraph presents the graphical tools to measure the classification accuracy of the score. We then define the different statistical measures to estimate the score performance. Finally, we consider the assessment tools when there is no response function.

Shannon entropy

Definition and properties The entropy is a measure of unpredictability or uncertainty of a random variable. Let \((X, Y)\) be a random vector where \( p_{i,j} = \text{Pr} \{ X = x_i, Y = y_j \} \), \( p_i = \text{Pr} \{ X = x_i \} \) and \( p_j = \text{Pr} \{ Y = y_j \} \). The Shannon entropy of the discrete random variable \( X \) is given by \(^{49}\):

\[
\mathcal{I}(X) = -\sum_{i=1}^{n} p_i \ln p_i
\]

We have the property \( 0 \leq \mathcal{I}(X) \leq \ln n \). The entropy is equal to zero if there is a state \( i \) such that \( p_i = 1 \) and is equal to \( \ln n \) in the case of the uniform distribution \( (p_i = 1/n) \). The Shannon entropy is a measure of the average information of the system. The lower the Shannon entropy, the more informative the system. For a random vector \((X, Y)\), we have:

\[
\mathcal{I}(X, Y) = -\sum_{i=1}^{n} \sum_{j=1}^{n} p_{i,j} \ln p_{i,j}
\]

We deduce that the conditional information of \( Y \) given \( X \) is equal to:

\[
\mathcal{I}(Y \mid X) = \mathbb{E}[\mathcal{I}(Y \mid X = x)] = -\sum_{i=1}^{n} \sum_{j=1}^{n} p_{i,j} \ln \frac{p_{i,j}}{p_i} = \mathcal{I}(X, Y) - \mathcal{I}(X)
\]

\(^{46}\) Alternative measures are \( \mathcal{M}(t, \delta) = 1 \{ S(t+\delta) - S(t) > \Delta^*_s \leq S(t) \} \) when we prefer to select companies among the best-in-class issuers and \( \mathcal{M}(t, \delta) = 1 \{ S(t+\delta) - S(t) > \Delta^*_s \geq S(t) \} \) when we want to detect worst-in-class issuers that will improve their ESG score.

\(^{49}\) We use the convention \( p_i \ln p_i = 0 \) when \( p_i \) is equal to zero.
We have the following properties:

- if $X$ and $Y$ are independent, we have $I(Y \mid X) = I(Y)$ and $I(X, Y) = I(Y) + I(X)$;
- if $X$ and $Y$ are perfectly dependent, we have $I(Y \mid X) = 0$ and $I(X, Y) = I(X)$.

The amount of information obtained about one random variable, through the other random variable is measured by the mutual information:

$$I(X \cap Y) = I(Y) + I(X) - I(X, Y)$$

$$= \sum_{i=1}^{n} \sum_{j=1}^{n} p_{i,j} \ln \frac{p_{i,j}}{p_i p_j}$$

Figure 2.21 shows some examples of Shannon entropy calculation. For each example, we indicate the probabilities $p_{i,j}$ and the values taken by $I(X)$, $I(Y)$, $I(X, Y)$ and $I(X \cap Y)$. The top/left panel corresponds to a diffuse system. The value of $I(X, Y)$ is maximum, meaning that the system is extremely disordered. The top/right panel represents a highly ordered system in the bivariate case and a diffuse system in the univariate case. We have $I(X \mid Y) = I(Y \mid X) = 0$, implying that the knowledge of $X$ is sufficient to find the state of $Y$. Generally, the system is not perfectly ordered or perfectly disordered. For instance, in the case of the system described in the bottom/left panel,
the knowledge of \( X \) informs us about the state of \( Y \). Indeed, if \( X \) is in the third state, then we know that \( Y \) cannot be in the first or sixth state. Another example is provided in the bottom/right panel.

**Remark 17** If we apply the Shannon entropy to the transition matrix of a Markov chain, we set \( X = \mathcal{R}(s) \) and \( Y = \mathcal{R}(t) \) where \( \mathcal{R}(t) \) is the state variable at the date \( t \). We obtain:

\[
I(\mathcal{R}(t) \mid \mathcal{R}(s)) = - \sum_{i=1}^{K} \pi_i^* \sum_{j=1}^{K} p_{i,j}^{(t-s)} \ln p_{i,j}^{(t-s)}
\]

where \( p_{i,j} = \Pr\{\mathcal{R}(t+1) = j \mid \mathcal{R}(t) = i\} \), \( K = \{1, 2, \ldots, K\} \) is the state space of the Markov chain and \( \pi^* \) is the associated stationary distribution.

**Application to scoring** Let \( S \) and \( Y \) be the score and the control variable. For instance, \( Y \) is a binary random variable that may indicate a bad ESG risk (\( Y = 0 \)) or a good ESG risk (\( Y = 1 \)). \( Y \) may also correspond to classes defined by some quantiles. With Shannon entropy, we can measure the information of the system \((S, Y)\). We can also compare two scores \( S_1 \) and \( S_2 \) by using the statistical measures \( I(S_1 \cap Y) \) and \( I(S_2 \cap Y) \). Let \( S_3 \) be the aggregated score obtained from the two individual scores \( S_1 \) and \( S_2 \). We can calculate the information contribution of each score with respect to the global score. Therefore, we can verify that a score really adds an information.

We consider the following decision rule:

\[
\left\{\begin{array}{l}
S \leq 0 \Rightarrow S^* = 0 \\
S > 0 \Rightarrow S^* = 1
\end{array}\right.
\]

We note \( n_{i,j} \) the number of observations such that \( S^* = i \) and \( Y = j \). We obtain the following system \((S^*, Y)\):

\[
\begin{array}{c|cc}
S^* & Y = 0 & Y = 1 \\
\hline
0 & n_{0,0} & n_{0,1} \\
1 & n_{1,0} & n_{1,1}
\end{array}
\]

where \( n = n_{0,0} + n_{0,1} + n_{1,0} + n_{1,1} \) is the total number of observations. The hit rate is the ratio of good bets:

\[
H = \frac{n_{0,0} + n_{1,1}}{n}
\]

This statistic can be viewed as an information measure of the system \((S, Y)\). When there are more states, we can consider the Shannon entropy. In Figure 2.22, we report the contingency table of two scores \( S_1 \) and \( S_2 \) for 100 observations\(^{50}\). We have \( I(S_1 \cap Y) = 0.763 \) and \( I(S_2 \cap Y) = 0.636 \). We deduce that \( S_1 \) is more informative than \( S_2 \).

**Graphical methods**

We assume that the control variable \( Y \) can takes two values: \( Y = 0 \) corresponds to a bad risk (or bad signal) while \( Y = 1 \) corresponds to a good risk (or good signal). Gouriéroux (1992) introduced three graphical tools for assessing the quality of a score: the performance curve, the selection curve and the discrimination curve\(^{51}\). In the following, we assume that the probability \( \Pr\{Y = 1 \mid S \geq s\} \)

\(^{50}\) Each score is divided into 6 intervals \((s_1, \ldots, s_6)\) while the dependent variable is divided into 5 intervals \((y_1, \ldots, y_5)\).

\(^{51}\) See also Gouriéroux and Jasiak (2007).
is increasing with respect to the level $s \in [0,1]$, which corresponds to the rate of acceptance. We deduce that the decision rule is the following:

- if the score of the observation is above the threshold $s$, the observation is selected;
- if the score of the observation is below the threshold $s$, the observation is not selected.

If $s$ is equal to one, we select no observation. If $s$ is equal to zero, we select all the observations. In a scoring system, the threshold $s$ is given. Below, we assume that $s$ is varying and we analyze the relevance of the score with respect to this parameter.

**Performance curve, selection curve and discriminant curve** The performance curve is the parametric function $y = \mathcal{P}(x)$ defined by:

\[
\begin{align*}
    x(s) &= \Pr\{\mathcal{S} \geq s\} \\
    y(s) &= \frac{\Pr\{Y = 0 \mid \mathcal{S} \geq s\}}{\Pr\{Y = 0\}}
\end{align*}
\]

where $x(s)$ corresponds to the proportion of selected observations and $y(s)$ corresponds to the ratio between the proportion of selected bad risks and the proportion of bad risks in the population. The score is efficient if the ratio is below one. If $y(s) > 1$, the score selects more bad risks than those we can find in the population. If $y(s) = 1$, the score is random and the performance is equal to zero. In this case, the selected population is representative of the total population.

The selection curve is the parametric curve $y = \mathcal{S}(x)$ defined by:

\[
\begin{align*}
    x(s) &= \Pr\{\mathcal{S} \geq s\} \\
    y(s) &= \Pr\{\mathcal{S} \geq s \mid Y = 0\}
\end{align*}
\]

where $y(s)$ corresponds to the ratio of observations that are wrongly selected. By construction, we would like that the curve $y = \mathcal{S}(x)$ is located below the bisecting line $y = x$ in order to verify that $\Pr\{\mathcal{S} \geq s \mid Y = 0\} < \Pr\{\mathcal{S} \geq s\}$.

---

52 We assume that the score is based on the 0/1 normalization, but this assumption is not important since we can always map a general score into a 0/1 score.

53 In this case, we have $\Pr\{Y = 0 \mid \mathcal{S} \geq s\} > \Pr\{Y = 0\}$. 

Handbook of Sustainable Finance
Remark 18 The performance and selection curves are related as follows:\(^{54}\):

\[ S(x) = xP(x) \]

The discriminant curve is the parametric curve \( y = D(x) \) defined by:

\[ D(x) = g_1(g_0^{-1}(x)) \]

where:

\[ g_y(s) = \Pr\{S \geq s \mid Y = y\} \]

It represents the proportion of good risks in the selected population with respect to the proportion of bad risks in the selected population. The score is said to be discriminant if the curve \( y = D(x) \) is located above the bisecting line \( y = x \).

**Some properties** We first notice that the previous parametric curves do not depend on the probability distribution of the score \( S \), but only on the ranking of the observations. They are then invariant if we apply an increasing function to the score. Gouriéroux (1992) also established the following properties:

1. the performance curve (respectively, the selection curve) is located below the line \( y = 1 \) (respectively, the bisecting line \( y = x \)) if and only if \( \text{cov}(f(Y), g(S)) \geq 0 \) for any increasing functions \( f \) and \( g \);

2. the performance curve is increasing if and only if:

\[ \text{cov}(f(Y), g(S) \mid S \geq s) \geq 0 \]

for any increasing functions \( f \) and \( g \), and any threshold level \( s \);

3. the selection curve is convex if and only if \( \mathbb{E}[f(Y) \mid S = s] \) is increasing with respect to the threshold level \( s \) for any increasing function \( f \).

Remark 19 The first property is the least restrictive. It allows us to verify that the score \( S \) is better than a random score. We can show that \((3) \Rightarrow (2) \Rightarrow (1)\). The last property is then the most restrictive.

A score is perfect or optimal if there is a threshold level \( s^* \) such that \( \Pr\{Y = 1 \mid S \geq s^*\} = 1 \) and \( \Pr\{Y = 0 \mid S < s^*\} = 1 \). It separates the population between good and bad risks. Graphically, the selection curve of a perfect score is equal to:

\[ y = 1 \{x > \Pr\{Y = 1\}\} \cdot \left(1 + \frac{x - 1}{\Pr\{Y = 0\}}\right) \]

\(^{54}\)We have:

\[
\Pr\{S \geq s \mid Y = 0\} = \frac{\Pr\{S \geq s, Y = 0\}}{\Pr\{Y = 0\}} \\
= \Pr\{S \geq s\} \cdot \frac{\Pr\{S \geq s, Y = 0\}}{\Pr\{S \geq s\} \Pr\{Y = 0\}} \\
= \Pr\{S \geq s\} \cdot \frac{\Pr\{Y = 0 \mid S \geq s\}}{\Pr\{Y = 0\}}
\]
Using the relationship $\mathcal{S}(x) = x \mathcal{P}(x)$, we deduce that the performance curve of a perfect score is given by:

$$y = \mathbb{I}\{x > \Pr\{Y = 1\}\} \cdot \left(\frac{x - \Pr\{Y = 1\}}{x \cdot \Pr\{Y = 0\}}\right)$$

For the discriminant curve, a perfect score satisfies $\mathcal{D}(x) = 1$. When the score is random, we have $\mathcal{S}(x) = \mathcal{D}(x) = x$ and $\mathcal{P}(x) = 1$. In Figure 2.23, we have reported the performance, selection and discriminant curves of a given score $\mathcal{S}$. We also show the curves obtained with an optimal (or perfect) score and a random score. A score must be located in the area between the curve computed with a random score and the curve computed with a perfect score, except if the score ranks the observations in a worst way than a random score.

Gouriéroux (1992) also established two properties for comparing two scores $\mathcal{S}_1$ and $\mathcal{S}_2$:

- the score $\mathcal{S}_1$ is more performing on the population $P_1$ than the score $\mathcal{S}_2$ on the population $P_2$ if and only if the performance (or selection) curve of $(\mathcal{S}_1, P_1)$ is below the performance (or selection) curve of $(\mathcal{S}_2, P_2)$;

- the score $\mathcal{S}_1$ is more discriminatory on the population $P_1$ than the score $\mathcal{S}_2$ on the population $P_2$ if and only if the discriminant curve of $(\mathcal{S}_1, P_1)$ is above the discriminant curve of $(\mathcal{S}_2, P_2)$.

Figure 2.24 illustrates the case where the score $\mathcal{S}_1$ is better than the score $\mathcal{S}_2$. However, the order is only partial. Most of the time, the two scores cannot be globally compared. An example is provided in Figure 2.25. The second score is not very good to distinguish good and bad risks when it takes small values, but it is close to a perfect score when it takes high values.
Chapter 2. ESG Scoring

Figure 2.24: The score $S_1$ is better than the score $S_2$

Performance curve

Selection curve

Discriminant curve

Figure 2.25: Illustration of the partial ordering between two scores
Statistical methods

Since the quantitative tools for comparing two scores are numerous, we focus on two non-parametric measures: the Kolmogorov-Smirnov test and the Gini coefficient.

Kolmogorov-Smirnov test

We consider the cumulative distribution functions:

\[ F_0(s) = \Pr \{ S \leq s \mid Y = 0 \} \]

and:

\[ F_1(s) = \Pr \{ S \leq s \mid Y = 1 \} \]

The score \( S \) is relevant if we have the stochastic dominance order \( F_0 \succ F_1 \). In this case, the score quality is measured by the Kolmogorov-Smirnov statistic:

\[ KS = \max_s |F_0(s) - F_1(s)| \]

It takes the value 1 if the score is perfect. The KS statistic may be used to verify that the score is not random. We then test the assumption \( H_0 : KS = 0 \) by using the tabulated critical values. In Figure 2.26, we give an example with 5,000 observations. The KS statistic is equal to 36%, which implies that \( H_0 \) is rejected at the confidence level 1%.

Gini coefficient

The Lorenz curve

The Gini coefficient is the statistic, which is the most used for measuring the performance of a score. It is related to the concept of Lorenz curve, which is a graphical representation of the concentration. Let \( X \) and \( Y \) be two random variables. The Lorenz curve \( y = L(x) \) is the parametric curve defined by:

\[
\begin{align*}
    x &= \Pr \{ X \leq x \} \\
    y &= \Pr \{ Y \leq y \mid X \leq x \}
\end{align*}
\]

In economics, \( x \) represents the proportion of individuals that are ranked by income while \( y \) represents the proportion of income. In this case, the Lorenz curve is a graphical representation of the distribution of income and is used for illustrating inequality of the wealth distribution between individuals. For example, we observe that 70% of individuals have only 34% of total income in Figure 2.27.

Definition of the Gini coefficient

The Lorenz curve has two limit cases. If the wealth is perfectly concentrated, one individual holds 100% of the total wealth. If the wealth is perfectly allocated between all the individuals, the corresponding Lorenz curve is the bisecting line. We define the Gini coefficient by:

\[ Gini(L) = \frac{A}{A + B} \]

The critical values at the 5% confidence level are equal to:

<table>
<thead>
<tr>
<th>n</th>
<th>CV</th>
</tr>
</thead>
<tbody>
<tr>
<td>10</td>
<td>40.9%</td>
</tr>
<tr>
<td>50</td>
<td>18.8%</td>
</tr>
<tr>
<td>100</td>
<td>13.4%</td>
</tr>
<tr>
<td>500</td>
<td>6.0%</td>
</tr>
<tr>
<td>5000</td>
<td>1.9%</td>
</tr>
</tbody>
</table>

More generally, the null hypothesis is rejected at the confidence level \( \alpha \) if we have:

\[ KS > \sqrt{\frac{1}{2n} \ln \left( \frac{2}{\alpha} \right)} \]
Figure 2.26: Comparison of the distributions $F_0(s)$ and $F_1(s)$

- **Performance curve**
- **Selection curve**
- **Discriminant curve**
- **Conditional CDF**

Figure 2.27: An example of Lorenz curve
where \( A \) is the area between the Lorenz curve and the curve of perfect equality, and \( B \) is the area between the curve of perfect concentration and the Lorenz curve. By construction, we have \( 0 \leq Gini(\mathcal{L}) \leq 1 \). The Gini coefficient is equal to zero in the case of perfect equality and one in the case of perfect concentration. We have:

\[
Gini(\mathcal{L}) = 1 - 2 \int_0^1 \mathcal{L}(x) \, dx
\]

**Application to scoring** We can interpret the selection curve as a Lorenz curve. We recall that \( F(s) = \Pr\{S \leq s\} \), \( F_0(s) = \Pr\{S \leq s \mid Y = 0\} \) and \( F_1(s) = \Pr\{S \leq s \mid Y = 1\} \). The selection curve is defined by the following parametric coordinates:

\[
\begin{align*}
  x(s) &= 1 - F(s) \\
  y(s) &= 1 - F_0(s)
\end{align*}
\]

The selection curve measures the capacity of the score for not selecting bad risks. We could also build the Lorenz curve that measures the capacity of the score for selecting good risks:

\[
\begin{align*}
  x(s) &= \Pr\{S \geq s\} = 1 - F(s) \\
  y(s) &= \Pr\{S \geq s \mid Y = 1\} = 1 - F_1(s)
\end{align*}
\]

It is called the precision curve. Another popular graphical tool is the receiver operating characteristic (or ROC) curve (Powers, 2011), which is defined by:

\[
\begin{align*}
  x(s) &= \Pr\{S \geq s \mid Y = 0\} = 1 - F_0(s) \\
  y(s) &= \Pr\{S \geq s \mid Y = 1\} = 1 - F_1(s)
\end{align*}
\]

An example for a given score \( S \) is provided in Figure 2.28. For all the three curves, we can calculate the Gini coefficient. Since the precision and ROC curves are located above the bisecting line, the Gini coefficient associated to the Lorenz curve \( \mathcal{L} \) becomes\(^{56}\):

\[
Gini(\mathcal{L}) = 2 \int_0^1 \mathcal{L}(x) \, dx - 1
\]

The Gini coefficient of the score \( S \) is then computed as follows:

\[
Gini^*(S) = \frac{Gini(\mathcal{L})}{Gini(\mathcal{L}^*)}
\]

where \( \mathcal{L}^* \) is the Lorenz curve associated to the perfect score.

**Remark 20** The Gini coefficient is not necessarily the same for the three curves. However, if the population is homogeneous, we generally obtain very similar figures\(^ {57}\).

\(^{56}\)An alternative to the Gini coefficient is the AUC measure, which corresponds to the area under the ROC curve. However, they give the same information since they are related by the equation:

\[
Gini(\text{ROC}) = 2 \times \text{AUC(ROC)} - 1
\]

\(^{57}\)For instance, we obtain the following results with the score \( S \) that has been used in Figure 2.28:

<table>
<thead>
<tr>
<th>Curve</th>
<th>Gini((\mathcal{L}))</th>
<th>Gini((\mathcal{L}^*))</th>
<th>Gini(^*(S))</th>
</tr>
</thead>
<tbody>
<tr>
<td>Selection</td>
<td>20.41%</td>
<td>40.02%</td>
<td>51.01%</td>
</tr>
<tr>
<td>Precision</td>
<td>30.62%</td>
<td>59.98%</td>
<td>51.05%</td>
</tr>
<tr>
<td>ROC</td>
<td>51.03%</td>
<td>100.00%</td>
<td>51.03%</td>
</tr>
</tbody>
</table>
Choice of the optimal cut-off The choice of the optimal cut-off $s^*$ depends on the objective function. For instance, we can calibrate $s^*$ in order to achieve a minimum universe size of ESG assets. We can also fix a given selection rate. From a statistical point of view, we must distinguish the construction of the scoring model and the decision rule. In statistical learning, we generally consider three datasets: the training set, the validation set and the test set. The training set is used for calibrating the model and its parameters whereas the validation set helps to avoid overfitting. But the decision rule is based on the test set.

Confusion matrix A confusion matrix is a special case of contingency matrix. Each row of the matrix represents the frequency in a predicted class while each column represents the frequency in an actual class. Using the test set, it takes the following form:

<table>
<thead>
<tr>
<th></th>
<th>$Y = 0$</th>
<th>$Y = 1$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$S &lt; s$</td>
<td>$n_{0,0}$</td>
<td>$n_{0,1}$</td>
</tr>
<tr>
<td>$S \geq s$</td>
<td>$n_{1,0}$</td>
<td>$n_{1,1}$</td>
</tr>
</tbody>
</table>

where $n_{i,j}$ represents the number of observations of the cell $(i,j)$. The interpretation of the confusion matrix is given in Table 2.16. The cells $(S < s, Y = 0)$ and $(S \geq s, Y = 1)$ correspond to observations that are well-classified: true negative (TN) and true positive (TP). The cells $(S \geq s, Y = 0)$ and $(S < s, Y = 1)$ correspond to two types of errors:

1. a false positive (FP) can induce a future loss, because the risk can materialize: this is a type I error;
2. a false negative (FN) potentially corresponds to a an opportunity cost: this is a type II error.
Chapter 2. ESG Scoring

Table 2.16: Interpretation of the confusion matrix

<table>
<thead>
<tr>
<th></th>
<th>$Y = 0$</th>
<th>$Y = 1$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$S &lt; s$</td>
<td>It is rejected and it is a bad risk (true negative)</td>
<td>It is rejected, but it is a good risk (false negative)</td>
</tr>
<tr>
<td>$S \geq s$</td>
<td>It is accepted, but it is a bad risk (false positive)</td>
<td>It is accepted and it is a good risk (true positive)</td>
</tr>
</tbody>
</table>

Classification ratios Binary classification defines many metrics for measuring the performance of the classifier (Fawcett, 2006):

- True Positive Rate $\text{TPR} = \frac{TP}{TP + FN}$
- False Negative Rate $\text{FNR} = \frac{FN}{FN + TP} = 1 - \text{TPR}$
- True Negative Rate $\text{TNR} = \frac{TN}{TN + FP}$
- False Positive Rate $\text{FPR} = \frac{FP}{FP + TN} = 1 - \text{TNR}$

The true positive rate (TPR) is also known as the sensitivity or the recall. It measures the proportion of real good risks that are correctly predicted good risk. Fawcett (2006) also defines the precision or the positive predictive value (PPV):

$$\text{PPV} = \frac{TP}{TP + FP}$$

It measures the proportion of predicted good risks that are correctly real good risk. Besides these metrics, statisticians also use two generic metrics:

1. The accuracy considers the classification of both negatives and positives:

$$\text{ACC} = \frac{TP + TN}{P + N} = \frac{TP + TN}{TP + FN + TN + FP}$$

2. The $F_1$ score is the harmonic mean of precision and sensitivity:

$$F_1 = \frac{2}{1/\text{precision} + 1/\text{sensitivity}} = \frac{2 \cdot \text{PPV} \cdot \text{TPR}}{\text{PPV} + \text{TPR}}$$

---

We rewrite the confusion matrix as follows:

<table>
<thead>
<tr>
<th></th>
<th>$Y = 0$</th>
<th>$Y = 1$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$S &lt; s$</td>
<td>$\text{TN}$</td>
<td>$\text{FN}$</td>
</tr>
<tr>
<td>$S \geq s$</td>
<td>$\text{FP}$</td>
<td>$\text{TP}$</td>
</tr>
</tbody>
</table>

$N = \text{TN} + \text{FP}$, $P = \text{FN} + \text{TP}$
Example 7 We consider three scoring systems that have been calibrated on a training set. These systems produce a score between 0 and 1000. A low value predicts a bad risk while a high value predicts a good risk. In order to calibrate the cut-off, we consider a test set, which is composed of 10000 new observations. In Table 2.17, we report the confusion matrix of each scoring system for different cut-off values (100, 200 and 500).

Table 2.17: Confusion matrix of three scoring systems and three cut-off values $s$

<table>
<thead>
<tr>
<th>Score</th>
<th>$s = 100$</th>
<th>$s = 200$</th>
<th>$s = 500$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$S_1$</td>
<td>386 616</td>
<td>698 1304</td>
<td>1330 3672</td>
</tr>
<tr>
<td></td>
<td>1614 7384</td>
<td>1302 6696</td>
<td>670 4328</td>
</tr>
<tr>
<td>$S_2$</td>
<td>372 632</td>
<td>700 1304</td>
<td>1386 3616</td>
</tr>
<tr>
<td></td>
<td>1628 7368</td>
<td>1300 6696</td>
<td>614 4384</td>
</tr>
<tr>
<td>$S_3$</td>
<td>382 616</td>
<td>656 1344</td>
<td>1378 3624</td>
</tr>
<tr>
<td></td>
<td>1618 7384</td>
<td>1344 6656</td>
<td>622 4376</td>
</tr>
<tr>
<td>Perfect</td>
<td>1000 - 0</td>
<td>2000 - 0</td>
<td>2000 - 3000</td>
</tr>
<tr>
<td></td>
<td>1000 8000</td>
<td>0 8000</td>
<td>0 5000</td>
</tr>
</tbody>
</table>

Using confusion matrices given in Table 2.17, we calculate the different classification ratios and report them in Table 2.18. In addition to the three scoring systems, we have also considered a perfect score in order to show what the best value is for each classification ratio, and we indicate the best scoring system. We notice that it depends on the ratio and on the value of the cut-off. For instance, if we want to maximize the true positive ratio or minimize the false negative ratio, $S_1$ is the best scoring system for low value of $s$ while $S_2$ is better when $s$ is equal to 500. For the other ratios, $S_1$ seems to be the best scoring system when $s = 100$, otherwise $S_2$ dominates $S_1$ and $S_3$ when $s = 200$ or $s = 500$.

Table 2.18: Binary classification ratios (in %) of the three scoring systems

<table>
<thead>
<tr>
<th>Score</th>
<th>$s$</th>
<th>TPR</th>
<th>FNR</th>
<th>TNR</th>
<th>FPR</th>
<th>PPV</th>
<th>ACC</th>
<th>$F_1$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$S_1$</td>
<td>100</td>
<td>92.3</td>
<td>7.7</td>
<td>19.3</td>
<td>80.7</td>
<td>82.1</td>
<td>77.7</td>
<td>86.9</td>
</tr>
<tr>
<td></td>
<td>200</td>
<td>83.7</td>
<td>16.3</td>
<td>34.9</td>
<td>65.1</td>
<td>83.7</td>
<td>73.9</td>
<td>83.7</td>
</tr>
<tr>
<td></td>
<td>500</td>
<td>54.1</td>
<td>45.9</td>
<td>66.5</td>
<td>33.5</td>
<td>86.6</td>
<td>56.6</td>
<td>66.6</td>
</tr>
<tr>
<td>$S_2$</td>
<td>100</td>
<td>92.1</td>
<td>7.9</td>
<td>18.6</td>
<td>81.4</td>
<td>81.9</td>
<td>77.4</td>
<td>86.7</td>
</tr>
<tr>
<td></td>
<td>200</td>
<td>83.7</td>
<td>16.3</td>
<td>35.0</td>
<td>65.0</td>
<td>83.7</td>
<td>74.0</td>
<td>83.7</td>
</tr>
<tr>
<td></td>
<td>500</td>
<td>54.8</td>
<td>45.2</td>
<td>69.3</td>
<td>30.7</td>
<td>87.7</td>
<td>57.7</td>
<td>67.5</td>
</tr>
<tr>
<td>$S_3$</td>
<td>100</td>
<td>92.8</td>
<td>7.1</td>
<td>19.1</td>
<td>80.9</td>
<td>82.0</td>
<td>77.1</td>
<td>86.9</td>
</tr>
<tr>
<td></td>
<td>200</td>
<td>83.2</td>
<td>16.8</td>
<td>32.8</td>
<td>67.2</td>
<td>83.2</td>
<td>73.1</td>
<td>83.2</td>
</tr>
<tr>
<td></td>
<td>500</td>
<td>54.7</td>
<td>45.3</td>
<td>68.9</td>
<td>31.1</td>
<td>87.6</td>
<td>57.5</td>
<td>67.3</td>
</tr>
<tr>
<td>Perfect</td>
<td>100</td>
<td>100.0</td>
<td>0</td>
<td>50.0</td>
<td>50.0</td>
<td>88.9</td>
<td>90.0</td>
<td>94.1</td>
</tr>
<tr>
<td></td>
<td>200</td>
<td>100.0</td>
<td>0</td>
<td>100.0</td>
<td>0</td>
<td>100.0</td>
<td>100.0</td>
<td>100.0</td>
</tr>
<tr>
<td></td>
<td>500</td>
<td>62.5</td>
<td>37.5</td>
<td>100.0</td>
<td>0</td>
<td>100.0</td>
<td>70.0</td>
<td>76.9</td>
</tr>
</tbody>
</table>

| Best  score | 100 | $S_1 / S_3$ | $S_1 / S_3$ | $S_1$ | $S_1$ | $S_1$ | $S_1$ |
| system | 200 | $S_1 / S_2$ | $S_1 / S_2$ | $S_2$ | $S_2$ | $S_2$ | $S_2$ |
| 500    | $S_2$ | $S_2$ | $S_2$ | $S_2$ | $S_2$ | $S_2$ | $S_2$ |

Remark 21 We recall that $F_0 (s) = \Pr \{ S \leq s \mid Y = 0 \}$ and $F_1 (s) = \Pr \{ S \leq s \mid Y = 1 \}$. We deduce that $TNR = F_0 (s)$, $FNR = F_1 (s)$, $FPR = 1 - F_0 (s)$ and $TPR = 1 - F_1 (s)$. Therefore,
the ROC curve is the parametric curve, where the $x$-coordinates are the false positive rates and the $y$-coordinates are the true positive rates. Generally, we note $\alpha$ and $\beta$ the type I and II errors. We may also interpret the ROC curve as the relationship of $1 - \beta(s)$ with respect to $\alpha(s)$.

Backtesting of unsupervised scoring systems


**Illustration with a sovereign ESG score**

Chapter 2. ESG Scoring

2.3 Rating system

As we have seen, a scoring model provides an automatic and statistical score. It is a pure quantitative approach. There may be the intervention of an analyst, but it is limited to data quality checks or forcing of input data\textsuperscript{59}. A rating (or a notation) is different from a score, because it implies a quality scale. Since it implies a value judgement, a rating is generally produced by an analyst. For example, this is the case of credit ratings, which are made by an analyst who takes into account several quantitative scores, qualitative data, private and meeting information. Nevertheless, the balance between quantitative and qualitative judgements depends on the type of issuers. For retail borrowers, the rating is mainly explained by the scoring model. For blue chip and mega-cap companies, the rating highly depends on the qualitative assessment of the credit risk. If we consider ESG risk, the rating process shares similar patterns. The ESG score is generally the key component of the ESG rating. It is validated by an extra-financial analyst and it may be\textit{ forced} based on his qualitative information and experience. This explains why extra-financial analysis is organized with respect to sectors. An ESG analyst, who is specialized in a given sector, can then have a better view of all the ratings produced for this sector. This is particularly true for the strategic sectors: automobiles, coal, cement, oil & gas, fertilizers & agricultural chemicals, utilities, etc. Nevertheless, there is a strong difference between credit and ESG rating processes from an investor viewpoint. Indeed, the number of rated companies for ESG analysis bears no comparison with the number of rated companies for credit analysis, because only few corporates have access to bond markets. On the contrary, a comprehensive ESG rating system must encompass all the securities and assets, notably all listed corporates and some private companies. In this context, the impact and the implication of the extra-financial analyst decrease with the firm size. This is why there is a strong small size bias in ESG rating systems.

2.3.1 Definition

ESG rating systems are based on the terminology of credit ratings (Box 2.4). For example, MSCI (2022) uses a 7-grade rating scale based on the grades AAA, AA, A, BBB, BB, B and CCC (Table 2.19). The number of grades, the rating symbols (letter, numeric) and the ordering of the system (low/worst rating to high/best rating vs. high/best to low/worst rating) differs from one provider to another provider\textsuperscript{60}:

- Amundi: A (high), B,... to G (low) — 7-grade scale
- FTSE Russell: 0 (low), 1,... to 5 (high) — 6-grade scale
- ISS ESG: 1 (high), 2,... to 10 (low) — 10-grade scale
- MSCI: AAA (high), AA,... to CCC (low) — 7-grade scale
- Refinitiv: A+ (high), A, A-, B+,... to D- (low) — 12-grade scale
- RepRisk: AAA (high), AA,... to D (low) — 8-grade scale
- Sustainalytics: 1 (low), 2,... to 5 (high) — 5-grade scale

We notice the high heterogeneity of rating scales. Nevertheless, we observe that they are less granular than those used by credit rating agencies. On average, an ESG rating system is made up of 7 grades vs. 20 grades for a credit rating system.

\textsuperscript{59}In some cases, the analyst may also validate the score.

\textsuperscript{60}In this list, we have included the asset manager Amundi, because ESG ratings are not only built by ESG rating agencies. Some investors (asset owners and managers) have defined their own internal ESG ratings.
Box 2.4: Terminology of credit ratings

A rating system is a symbolic or numeric classification according to grade, which indicates a degree or step in a scale. For example, the credit rating systems of S&P, Moody’s and Fitch is reported in Table 2.B. They are all based on a rating scale of 20 grades. The symbolic rank AA+ (or BBB) is then a grade or a rating in the S&P classification. A notch means the difference between a particular rating and the next lower. For example, in the case of Moody’s, the difference between Baa1 and Baa2 constitutes one Notch, whereas the difference between Aaa and Aa2 corresponds to two notches. When a credit rating agency revises the credit risk of a company, it may upgrade its rating by one notch (+1 notch), two notches (+2 notches), etc. or it may downgrade its rating by one notch (−1 notch), two notches (−2 notches), etc.

Table 2.B: Credit rating system of S&P, Moody’s and Fitch

<table>
<thead>
<tr>
<th>Prime</th>
<th>High Grade</th>
<th>Upper</th>
<th>Lower</th>
</tr>
</thead>
<tbody>
<tr>
<td>S&amp;P/Fitch</td>
<td>AAA</td>
<td>AA+</td>
<td>AA</td>
</tr>
<tr>
<td>Moody’s</td>
<td>Aaa</td>
<td>Aa1</td>
<td>Aa2</td>
</tr>
<tr>
<td>Non Investment Grade</td>
<td>Speculative</td>
<td>Highly Speculative</td>
<td>Substantial Risk</td>
</tr>
<tr>
<td>S&amp;P/Fitch</td>
<td>BB+</td>
<td>BB</td>
<td>BB−</td>
</tr>
<tr>
<td>Moody’s</td>
<td>Ba1</td>
<td>Ba2</td>
<td>Ba3</td>
</tr>
</tbody>
</table>

*Or 21 grades if we include the issuer default. Nevertheless, D is not considered as a rating.

Remark 22 In the sequel, we use the 7-grade scale based on the ratings AAA, AA, A, BBB, BB, B and CCC. We think that it is easier to manipulate and understand from a pedagogical point of view. A company rated AAA is a good company (or a good ESG risk) and a company rated CCC is a bad company (or a bad ESG risk).

2.3.2 ESG rating process

The construction of ESG ratings follows the same process than credit ratings (Figure 2.29). We need to define the map function that converts an ESG score into an ESG rating. In the case of credit risk, the estimate of the one-year probability of default is converted into credit ratings. In the case of ESG risk, the ESG score is converted into an ESG rating such that the best scores correspond to the best ratings and the worst scores correspond to the worst ratings.

For instance, a CCC-rated company has a one-year probability of default of 25%; a B-rated company has a 5% probability to default in the next year; for a BB-rated company, the one-year probability of default is equal to 1%; etc.
Chapter 2. ESG Scoring

Figure 2.29: From ESG score to ESG rating

The first step consists in specifying the map function:

$$Map: \quad \Omega_S \rightarrow \Omega_R \quad S \mapsto R = Map(S)$$

where $$\Omega_S$$ is the support of ESG scores, $$\Omega_R$$ is the ordered state space of ESG ratings and $$R$$ is the ESG rating. By construction, $$Map$$ is a monotone function in order to preserve the preference ordering. In the case where $$Map$$ is increasing, we verify that:

$$S_2 > S_1 \iff Map(S_2) > Map(S_1)$$

The second step is the validation (and the possible forcing) of the rating by the analyst.

Let us see some examples. MSCI (2022, page 12) explains that they use a uniform map function where $$\Omega_S = [0, 10]$$ and $$\Omega_R = \{CCC, B, BB, BBB, A, AA, AAA\}$$. The score is then divided into 7 equally-sized intervals and we have:

$$Map(s) = \begin{cases} 
CCC & \text{if } S \in [0, 10/7] \\
B & \text{if } S \in [10/7, 20/7] \\
BB & \text{if } S \in [20/7, 30/7] \\
BBB & \text{if } S \in [30/7, 40/7] \\
A & \text{if } S \in [40/7, 50/7] \\
AA & \text{if } S \in [50/7, 60/7] \\
AAA & \text{if } S \in [60/7, 10] 
\end{cases}$$

For instance, if the ESG score of the company is equal to 5, we assign the grade BBB, a score of 8 corresponds to the grade AA, etc. Refinitiv (2022, page 7) also considers a uniform map function, implying that $$\Omega_S$$ is divided by 12 equally-sized intervals:

“[...] 'D' score (D-, D and D+) indicates poor relative ESG performance and insufficient degree of transparency in reporting material ESG data publicly. 'C' score (C-, C and C+) indicates satisfactory relative ESG performance and moderate degree of transparency in reporting material ESG data publicly. 'B' score (B-, B and B+) indicates good relative ESG performance and above average degree of transparency in reporting material ESG data publicly. 'A' score (A-, A and A+) indicates excellent relative ESG performance and high degree of transparency in reporting material ESG data publicly.”

We assume that the map function is an increasing piecewise function, $$S \sim F$$ and $$S \in (s^-, s^+)$$.

We note $$s_1^*, \ldots, s_K^*$$ the knots of the piecewise function, $$K$$ the number of ratings and $$\Omega_R = \{R_1, \ldots, R_K\}$$ the set of grades. We set $$s_0^* = s^-$$ and $$s_K^* = s^+$$. We deduce that:

$$p_k = \Pr \{R = R_k\} = \Pr \{s_{k-1}^* \leq S < s_k^*\} = F(s_k^*) - F(s_{k-1}^*)$$

Handbook of Sustainable Finance
Using this equation, we can then compute the frequency distribution of the ratings. The set of frequencies \( \{p_1, \ldots, p_K\} \) is denoted by \( \mathbb{P} \). If we don’t know the distribution \( \mathbb{F} \), we consider the empirical distribution \( \hat{\mathbb{F}} \) and the estimated frequency is equal to \( \hat{p}_k = \hat{\mathbb{F}}(s^*_k) - \hat{\mathbb{F}}(s^*_{k-1}) \). If we would like to build a rating system with pre-defined frequencies \( (p_1, \ldots, p_K) \), we have to solve the following equation:

\[
\mathbb{F}(s^*_k) - \mathbb{F}(s^*_{k-1}) = p_k
\]

We deduce that:

\[
\mathbb{F}(s^*_k) = p_k + \mathbb{F}(s^*_{k-1}) = p_k + p_{k-1} + \mathbb{F}(s^*_{k-2}) = \left( \sum_{j=1}^{k} p_j \right) + \mathbb{F}(s^*_0)
\]

Since \( \mathbb{F}(s^*_0) = 0 \), we conclude that:

\[
s^*_k = \mathbb{F}^{-1}\left( \sum_{j=1}^{k} p_j \right)
\]

**Remark 23** The discrete probability space of the rating system is denoted by \( (\Omega_R, \Omega_R, \mathbb{P}) \) and we have:

\[
\mathcal{E} := \Omega_R \times \mathbb{P} = \{(R_1, p_1), \ldots, (R_K, p_K)\}
\]

Let us consider a uniform score \( S \sim \mathcal{U}_{[a,b]} \). We have \( \mathbb{F}(s) = (s - a) / (b - a) \). The rating system consists in \( K \) equally-sized intervals. The knots of the map function are then equal to:

\[
s^*_k = a + \frac{(b - a)}{K} k
\]

It follows that:

\[
p_k = \mathbb{F}\left( a + \frac{(b - a)}{K} k \right) - \mathbb{F}\left( a + \frac{(b - a)}{K} (k - 1) \right) = \frac{a + \frac{(b - a)}{K} k - a}{b - a} - \frac{a + \frac{(b - a)}{K} (k - 1) - a}{b - a} = \frac{1}{K}
\]

We obtain a trivial result: the rating frequencies are all equal. In the case where we impose predefined frequencies \( (p_1, \ldots, p_K) \), the knots of the map function are equal to:

\[
s^*_k = a + (b - a) \left( \sum_{j=1}^{k} p_j \right)
\]

If we consider a 0/100 uniform score, we deduce that \( s^*_k = 100 \cdot \sum_{j=1}^{k} p_j \). For example, if \( \Omega_R \times \mathbb{P} = \{\text{CCC}, 5\%\}, \text{(B}, 10\%\}, \text{(BB}, 20\%\}, \text{(BBB}, 30\%\}, \text{(A}, 20\%\}, \text{(AA}, 10\%\}, \text{(AAA}, 5\%\} \), we obtain the trivial piecewise function where \( s^*_\text{CCC} = 5 \), \( s^*_\text{B} = 15 \), \( s^*_\text{BB} = 35 \), \( s^*_\text{BBB} = 65 \), \( s^*_\text{A} = 85 \) and \( s^*_\text{AA} = 95 \).
Chapter 2. ESG Scoring

Figure 2.30: Map function of a $z$-score (equal-space ratings)

For a $z$-score system, we assume that $S \sim \mathcal{N}(0, 1)$ and we obtain:

$$p_k = \Phi (s_k^*) - \Phi (s_{k-1}^*)$$

If we consider the 7-grade rating system with the classical knots $(-2.5, -1.5, -0.5, 0.5, 1.5, 2.5)$, we obtain the map function given in Figure 2.30 where:

$$p_k = \Phi (-3.5 + k) - \Phi (-4.5 + k)$$

The rating system with equal frequencies is obtained by using the following knots:

$$s_k^+ = \Phi^{-1} \left( \frac{k}{K} \right) \quad \text{for } k = 1, \ldots, K$$

In the case $K = 7$, the map function is given in Figure 2.31.

Figure 2.31: Map function of a $z$-score (equal-frequency ratings)

Remark 24 We recall that the role of the ESG analyst is to verify the consistency of the rated companies. This is why we generally observe forced ratings (or scores).

$62$ We have $F(s) = u \iff (s - a) / (b - a) = u$. We deduce that $s = F^{-1}(u) = a + (b - a) u$.

$63$ By construction, the knot $s_{AAA}^* = 100$ is not necessarily to be defined because we always have $s_{AAA}^* = s^+$. $64$ We obtain the following results: $p_{CCC} = \Phi (-2.5) = 0.62\%$, $p_B = \Phi (-1.5) - \Phi (-2.5) = 6.06\%$, $p_{BB} = \Phi (-0.5) - \Phi (-1.5) = 24.17\%$, $p_{BBB} = \Phi (0.5) - \Phi (-0.5) = 38.29\%$, $p_A = \Phi (1.5) - \Phi (0.5) = 24.17\%$, $p_{AA} = \Phi (2.5) - \Phi (1.5) = 6.06\%$ and $p_{AAA} = 1 - \Phi (2.5) = 0.62\%$. 

Handbook of Sustainable Finance
Chapter 2. ESG Scoring

109

Box 2.5: Asymmetric rating system

In a symmetric rating system, the probability of the $k^{th}$ rating class is equal to the probability of the $(K - k + 1)^{th}$ rating class, e.g., $p_{CCC} = p_{AAA}$, $p_{BB} = p_A$ and $p_{BB} = p_A$. To obtain an asymmetric rating system, the first approach is to define the frequencies $p_k$ such that $\exists k : p_k \neq p_{K-k+1}$. We note $P_{worst} = \sum_{k=1}^{\lfloor K/2 \rfloor} p_k$ and $P_{best} = \sum_{k=1}^{K/2} p_k$ the probability to be below and average the median rating. The rating process is said to be a losing-oriented system if $P_{worst} \geq P_{best}$, otherwise it is a winning-oriented system. This means that companies with bad ESG risk are more prevalent than companies with good ESG risk. For instance, $\Omega_R \times \mathbb{P} = \{(CCC, 5\%), (B, 10\%), (BB, 25\%), (BBB, 40\%), (A, 15\%), (AA, 4\%), (AAA, 1\%)\}$ is a losing-oriented system. The choice of an asymmetric rating system may be motivated by the underlying ESG strategy. For instance, implementing an exclusion ESG policy is not equivalent to considering a selection ESG policy. The investor may then want to adapt his rating system to take into account the objective of the strategy. The second approach to obtain an asymmetric rating system is to consider a $b$-score normalization with $\alpha \neq \beta$. Some examples are provided in Table 2.C.

Table 2.C: Frequency distribution of ESG ratings (in %)

| Parameters | Rating |
|------------|
| $\alpha$  | $\beta$ | CCC | B | BB | BBB | A | AA | AAA |
| 1 | 1 | 14.3 | 14.3 | 14.3 | 14.3 | 14.3 | 14.3 | 14.3 |
| 2 | 2 | 5.5 | 14.3 | 19.5 | 21.3 | 19.5 | 14.3 | 5.5 |
| 3 | 3 | 2.3 | 12.1 | 22.3 | 26.4 | 22.3 | 12.1 | 2.3 |
| 0.25 | 0.25 | 33.9 | 7.5 | 5.9 | 5.5 | 5.9 | 7.5 | 33.9 |
| 2.5 | 1.5 | 1.5 | 6.4 | 12.4 | 18.1 | 22.3 | 23.2 | 16.0 |
| 1.5 | 2.5 | 16.0 | 23.2 | 22.3 | 18.1 | 12.4 | 6.4 | 1.5 |
| 0.75 | 1 | 23.2 | 15.8 | 13.9 | 12.8 | 12.0 | 11.4 | 10.9 |

We reiterate that we only consider rating systems that satisfy a comprehensive preference ordering: $\forall k : R_k > R_{k-1}$.

2.3.3 Rating migration matrix

One important issue concerns the consistency of the rating system. In particular, we may wonder whether it is relevant to use an equal-frequency, an equal-space or an asymmetric rating scheme. In the case of credit rating systems, we generally observe that medium risk classes have a higher frequency than extreme (low/high) risk classes. For instance, there are more BBB-rated companies than CCC-rated companies, the less frequent class is by far the AAA rating (less than 1%), etc. In the case of ESG rating systems, there is no consensus. Therefore, to assess the consistency and robustness of the rating system, we need to use probabilistic tools based on transition probability matrices (Norris, 1997).

Discrete-time modeling

Markov chain model We consider a time-homogeneous Markov chain $\mathcal{R}$, whose transition matrix is $P = (p_{i,j})$. We note $\Omega_R = \{R_1, \ldots, R_K\}$ the state space of the chain and $\mathbb{K} = \{1, \ldots, K\}$ the corresponding index set. $p_{i,j}$ is the probability that the entity migrates from rating $R_i$ to rating $R_j$. 

Handbook of Sustainable Finance
The matrix $P$ satisfies the following properties:

- $\forall i, j \in \mathbb{K}, p_{i,j} \geq 0$;
- $\forall i \in \mathbb{K}, \sum_{j=1}^{K} p_{i,j} = 1$.

Let $\mathcal{R}(t)$ be the value of the state at time $t$. We define $p(s, i; t, j)$ as the probability that the entity reaches the state $R_j$ at time $t$ given that it has reached the state $R_i$ at time $s$. We have:

$$p(s, i; t, j) = \Pr \{ \mathcal{R}(t) = R_j \mid \mathcal{R}(s) = R_i \} = p^{(t-s)}_{i,j}$$

This probability only depends on the duration between $s$ and $t$ because of the Markov property. Therefore, we can restrict the analysis by calculating the $n$-step transition probability:

$$p^{(n)}_{i,j} = \Pr \{ \mathcal{R}(t+n) = R_j \mid \mathcal{R}(t) = R_i \}$$

and the associated $n$-step transition matrix $P^{(n)} = (p^{(n)}_{i,j})$. For $n = 2$, we obtain:

$$p^{(2)}_{i,j} = \Pr \{ \mathcal{R}(t+2) = R_j \mid \mathcal{R}(t) = R_i \}$$

$$= \sum_{k=1}^{K} \Pr \{ \mathcal{R}(t+2) = R_j, \mathcal{R}(t+1) = R_k \mid \mathcal{R}(t) = R_i \}$$

$$= \sum_{k=1}^{K} \Pr \{ \mathcal{R}(t+2) = R_j \mid \mathcal{R}(t+1) = R_k \} \cdot \Pr \{ \mathcal{R}(t+1) = R_k \mid \mathcal{R}(t) = R_i \}$$

$$= \sum_{k=1}^{K} p_{i,k} \cdot p_{k,j}$$

In a similar way, we obtain:

$$p^{(n+m)}_{i,j} = \sum_{k=1}^{K} p^{(n)}_{i,k} \cdot p^{(m)}_{k,j} \quad \forall n, m > 0 \quad (2.4)$$

This equation is called the forward Chapman-Kolmogorov equation. In matrix form, we have:

$$P^{(n+m)} = P^{(n)} \cdot P^{(m)}$$

with the convention $P^{(0)} = I$. In particular, we have:

$$P^{(n)} = P^{(n-1)} \cdot P^{(1)} = P^{(n-2)} \cdot P^{(1)} \cdot P^{(1)} = \prod_{t=1}^{n} P^{(1)} = P^n$$

We deduce that:

$$p(t, i; t + n, j) = p^{(n)}_{i,j} = e_i^T P^n e_j \quad (2.5)$$

When we apply this framework to ESG risk, $\mathcal{R}(t)$ denotes the rating (or the risk class) of the company at time $t$ and $p_{i,j}$ is the one-period transition probability from rating $R_i$ to rating $R_j$. 

Handbook of Sustainable Finance
In Table 2.20, we report an example of transition probability matrix. We read the figures as follows\(^5\); a company rated AAA has a one-year probability of 92.76% to remain AAA; its probability to become AA is 5.66%; a company rated CCC has a probability of 16.11% to improve its rating, etc. In Tables 2.21 and 2.22, we have reported the two-year and five-year transition matrices. We detail below the calculation of \(p_{\text{AAA,AAA}}^{(2)}\):

\[
p_{\text{AAA,AAA}}^{(2)} = p_{\text{AAA,AAA}} \times p_{\text{AAA,AAA}} + p_{\text{AAA,AA}} \times p_{\text{AA,AAA}} + p_{\text{AAA,A}} \times p_{\text{A,AAA}} + p_{\text{AAA,BBB}} \times p_{\text{BBB,AAA}} + p_{\text{AAA,BB}} \times p_{\text{BB,AAA}} + p_{\text{AAA,B}} \times p_{\text{B,AAA}} + p_{\text{AAA,CCC}} \times p_{\text{CCC,AAA}}
\]

\[
= 0.9276^2 + 0.0566 \times 0.0415 + 0.0090 \times 0.0018 + 0.0045 \times 0.0007 + 0.0023 \times 0.0004
\]

\[
= 86.28\%\]

Table 2.20: ESG migration matrix #1 (one-year transition probability in %)

<table>
<thead>
<tr>
<th></th>
<th>AAA</th>
<th>AA</th>
<th>A</th>
<th>BBB</th>
<th>BB</th>
<th>B</th>
<th>CCC</th>
</tr>
</thead>
<tbody>
<tr>
<td>AAA</td>
<td>92.76</td>
<td>5.66</td>
<td>0.90</td>
<td>0.45</td>
<td>0.23</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>AA</td>
<td>4.15</td>
<td>82.73</td>
<td>11.86</td>
<td>0.89</td>
<td>0.30</td>
<td>0.07</td>
<td>0.00</td>
</tr>
<tr>
<td>A</td>
<td>0.18</td>
<td>15.47</td>
<td>72.98</td>
<td>10.46</td>
<td>0.82</td>
<td>0.09</td>
<td>0.00</td>
</tr>
<tr>
<td>BBB</td>
<td>0.07</td>
<td>1.32</td>
<td>19.60</td>
<td>69.49</td>
<td>9.03</td>
<td>0.42</td>
<td>0.07</td>
</tr>
<tr>
<td>BB</td>
<td>0.04</td>
<td>0.19</td>
<td>1.55</td>
<td>19.36</td>
<td>70.88</td>
<td>7.75</td>
<td>0.23</td>
</tr>
<tr>
<td>B</td>
<td>0.00</td>
<td>0.05</td>
<td>0.24</td>
<td>1.43</td>
<td>21.54</td>
<td>74.36</td>
<td>2.38</td>
</tr>
<tr>
<td>CCC</td>
<td>0.00</td>
<td>0.00</td>
<td>0.22</td>
<td>0.44</td>
<td>2.21</td>
<td>13.24</td>
<td>83.89</td>
</tr>
</tbody>
</table>

Table 2.21: Two-year transition probability in % (migration matrix #1)

<table>
<thead>
<tr>
<th></th>
<th>AAA</th>
<th>AA</th>
<th>A</th>
<th>BBB</th>
<th>BB</th>
<th>B</th>
<th>CCC</th>
</tr>
</thead>
<tbody>
<tr>
<td>AAA</td>
<td>86.28</td>
<td>10.08</td>
<td>2.25</td>
<td>0.92</td>
<td>0.44</td>
<td>0.02</td>
<td>0.00</td>
</tr>
<tr>
<td>AA</td>
<td>7.30</td>
<td>70.52</td>
<td>18.68</td>
<td>2.67</td>
<td>0.66</td>
<td>0.15</td>
<td>0.00</td>
</tr>
<tr>
<td>A</td>
<td>0.95</td>
<td>24.24</td>
<td>57.16</td>
<td>15.20</td>
<td>2.19</td>
<td>0.25</td>
<td>0.01</td>
</tr>
<tr>
<td>BBB</td>
<td>0.21</td>
<td>5.06</td>
<td>28.22</td>
<td>52.11</td>
<td>12.93</td>
<td>1.33</td>
<td>0.14</td>
</tr>
<tr>
<td>BB</td>
<td>0.09</td>
<td>0.79</td>
<td>6.07</td>
<td>27.45</td>
<td>53.68</td>
<td>11.37</td>
<td>0.55</td>
</tr>
<tr>
<td>B</td>
<td>0.01</td>
<td>0.18</td>
<td>0.98</td>
<td>6.26</td>
<td>31.47</td>
<td>57.28</td>
<td>3.82</td>
</tr>
<tr>
<td>CCC</td>
<td>0.00</td>
<td>0.05</td>
<td>0.50</td>
<td>1.32</td>
<td>6.31</td>
<td>21.13</td>
<td>70.70</td>
</tr>
</tbody>
</table>

Table 2.22: Five-year transition probability in % (migration matrix #1)

<table>
<thead>
<tr>
<th></th>
<th>AAA</th>
<th>AA</th>
<th>A</th>
<th>BBB</th>
<th>BB</th>
<th>B</th>
<th>CCC</th>
</tr>
</thead>
<tbody>
<tr>
<td>AAA</td>
<td>70.45</td>
<td>18.69</td>
<td>6.97</td>
<td>2.61</td>
<td>1.08</td>
<td>0.18</td>
<td>0.01</td>
</tr>
<tr>
<td>AA</td>
<td>13.13</td>
<td>50.21</td>
<td>26.03</td>
<td>7.90</td>
<td>2.22</td>
<td>0.48</td>
<td>0.03</td>
</tr>
<tr>
<td>A</td>
<td>4.35</td>
<td>33.20</td>
<td>37.78</td>
<td>17.99</td>
<td>5.52</td>
<td>1.08</td>
<td>0.09</td>
</tr>
<tr>
<td>BBB</td>
<td>1.50</td>
<td>16.49</td>
<td>32.49</td>
<td>30.90</td>
<td>14.61</td>
<td>3.63</td>
<td>0.38</td>
</tr>
<tr>
<td>BB</td>
<td>0.50</td>
<td>5.98</td>
<td>17.83</td>
<td>30.10</td>
<td>31.35</td>
<td>12.85</td>
<td>1.39</td>
</tr>
<tr>
<td>B</td>
<td>0.15</td>
<td>1.90</td>
<td>7.40</td>
<td>18.95</td>
<td>35.11</td>
<td>31.26</td>
<td>5.23</td>
</tr>
<tr>
<td>CCC</td>
<td>0.05</td>
<td>0.64</td>
<td>2.55</td>
<td>6.93</td>
<td>17.96</td>
<td>38.54</td>
<td>43.33</td>
</tr>
</tbody>
</table>

---

\(^5\) The rows represent the initial rating whereas the columns indicate the final rating.
We note $\pi_k^{(n)}$ the probability of the state $R_k$ at time $n$:

$$\pi_k^{(n)} = \Pr \{ R(n) = R_k \}$$

and $\pi^{(n)} = \left( \pi_1^{(n)}, \ldots, \pi_K^{(n)} \right)$ the probability distribution. By construction, we have:

$$\pi^{(n+1)} = P^\top \pi^{(n)}$$

The Markov chain $R$ admits a stationary distribution $\pi^*$ if

$$\pi^* = P^\top \pi^*$$

In this case, $\pi_k^*$ is the limiting probability of state $R_k$:

$$\lim_{n \to \infty} p_{i,k}^{(n)} = \pi_k^* \quad \forall i$$

We can interpret $\pi_k^*$ as the average duration spent by the chain $R$ in the state $R_k$. Let $T_k$ be the return period of state $R_k$:

$$T_k = \inf \{ n : R(n) = R_k \mid R(0) = R_k \}$$

The average return period is then equal to:

$$\tau_k := \mathbb{E} [T_k] = \frac{1}{\pi_k}$$

---

*Not all Markov chains behave in this way, meaning that $\pi^*$ does not necessarily exist.

$^b$ $T_k$ is a stopping time. It is also called the first-passage time.

---

We compute the stationary distribution$^{66}$ and we obtain:

$$\pi^* = (17.78\%, 29.59\%, 25.12\%, 15.20\%, 8.35\%, 3.29\%, 0.67\%)$$

The average return periods are then equal to 5.6, 3.4, 4.0, 6.6, 12.0, 30.4 and 149.0 years. The interpretation of these results is the following. In the long term, the probability to observe a AAA-rated company is equal to 17.78%, while the probability to observe a CCC-rated company is equal to 0.67%. The probability $\pi_k^*$ is then the long-term equivalent of the current (or sample) frequency $p_k$. Similarly, the expected time to reach the worst-in-class state is equal to 149 years. These results show that the rating system #1 is clearly a winning-oriented system, where more than 70% of corporates are expected to have a rating above BBB.

---

$^{66}$There are three numerical approaches to compute $\pi^*$. The first one is to approximate $P^{(\infty)}$ by $P^{(n)}$ with $n$ sufficient large ($n > 100$) and take any rows of the matrix $P^{(\infty)}$. The second method is to compute the eigendecomposition $V A V^{-1}$ of $P^\top$ and return the left eigenvector whose eigenvalue is exactly equal to 1. This second approach uses the fact that $\pi^* = P^\top \pi^*$ defines an eigenvalue problem $(P^\top - \lambda I_K) \pi^* = 0$ with $\lambda = 1$. Finally, the third method directly solves the equation $(P^\top - I_K) \pi^* = 0$ by computing an orthonormal basis for the null space of $P^\top - I_K$. For the last two methods, we normalize the solution such that $1^\top \pi^* = 1$. 

---

*Handbook of Sustainable Finance*
These results show that the rating system #2 is a balanced system, implying that the average return periods are equal to different. Indeed, the second rating system is more reactive than the first rating system. If we compute the stationary distribution of the second rating system, we obtain:\[\pi^* = (3.11\%, 10.10\%, 17.46\%, 27.76\%, 25.50\%, 12.68\%, 3.39\%)\] implying that the average return periods are equal to 32.2, 9.9, 5.7, 3.6, 3.9, 7.9 and 29.5 years. These results show that the rating system #2 is a balanced system.

Table 2.23: ESG migration matrix #2 (one-month transition probability in %)

<table>
<thead>
<tr>
<th></th>
<th>AAA</th>
<th>AA</th>
<th>A</th>
<th>BBB</th>
<th>BB</th>
<th>B</th>
<th>CCC</th>
</tr>
</thead>
<tbody>
<tr>
<td>AAA</td>
<td>93.50</td>
<td>5.00</td>
<td>0.50</td>
<td>0.50</td>
<td>0.50</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>AA</td>
<td>2.00</td>
<td>93.00</td>
<td>4.00</td>
<td>0.50</td>
<td>0.50</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>A</td>
<td>0.00</td>
<td>3.00</td>
<td>93.00</td>
<td>3.90</td>
<td>0.10</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>BBB</td>
<td>0.00</td>
<td>0.10</td>
<td>2.80</td>
<td>94.00</td>
<td>3.00</td>
<td>0.10</td>
<td>0.00</td>
</tr>
<tr>
<td>BB</td>
<td>0.00</td>
<td>0.00</td>
<td>0.10</td>
<td>3.50</td>
<td>94.50</td>
<td>1.80</td>
<td>0.10</td>
</tr>
<tr>
<td>B</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.10</td>
<td>3.70</td>
<td>96.00</td>
<td>0.20</td>
</tr>
<tr>
<td>CCC</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.40</td>
<td>0.50</td>
<td>0.60</td>
<td>98.50</td>
</tr>
</tbody>
</table>

In Table 2.23, we now consider the ESG migration matrix #2, which has been computed on a monthly basis. If we would like to compare the two rating systems, we can compute the one-year probability transition matrix (Table 2.24). We observe that the two transition matrices are very different. Indeed, the second rating system is more reactive than the first rating system. If we compute the stationary distribution of the second rating system, we obtain:\[\pi^* = (3.11\%, 10.10\%, 17.46\%, 27.76\%, 25.50\%, 12.68\%, 3.39\%)\] implying that the average return periods are equal to 32.2, 9.9, 5.7, 3.6, 3.9, 7.9 and 29.5 years. These results show that the rating system #2 is a balanced system.

Table 2.24: One-year probability transition in % (migration matrix #2)

<table>
<thead>
<tr>
<th></th>
<th>AAA</th>
<th>AA</th>
<th>A</th>
<th>BBB</th>
<th>BB</th>
<th>B</th>
<th>CCC</th>
</tr>
</thead>
<tbody>
<tr>
<td>AAA</td>
<td>48.06</td>
<td>29.71</td>
<td>10.34</td>
<td>6.42</td>
<td>4.95</td>
<td>0.49</td>
<td>0.03</td>
</tr>
<tr>
<td>AA</td>
<td>11.65</td>
<td>49.25</td>
<td>24.10</td>
<td>9.60</td>
<td>4.87</td>
<td>0.49</td>
<td>0.03</td>
</tr>
<tr>
<td>A</td>
<td>2.02</td>
<td>17.51</td>
<td>49.67</td>
<td>24.72</td>
<td>5.52</td>
<td>0.54</td>
<td>0.03</td>
</tr>
<tr>
<td>BBB</td>
<td>0.27</td>
<td>3.53</td>
<td>17.46</td>
<td>55.50</td>
<td>20.21</td>
<td>2.88</td>
<td>0.16</td>
</tr>
<tr>
<td>BB</td>
<td>0.03</td>
<td>0.60</td>
<td>4.21</td>
<td>23.43</td>
<td>57.45</td>
<td>13.27</td>
<td>1.01</td>
</tr>
<tr>
<td>B</td>
<td>0.00</td>
<td>0.08</td>
<td>0.74</td>
<td>5.94</td>
<td>27.10</td>
<td>64.18</td>
<td>1.96</td>
</tr>
<tr>
<td>CCC</td>
<td>0.00</td>
<td>0.07</td>
<td>0.57</td>
<td>4.22</td>
<td>5.77</td>
<td>5.85</td>
<td>83.51</td>
</tr>
</tbody>
</table>

Table 2.25: One-month probability transition in % (migration matrix #1)

<table>
<thead>
<tr>
<th></th>
<th>AAA</th>
<th>AA</th>
<th>A</th>
<th>BBB</th>
<th>BB</th>
<th>B</th>
<th>CCC</th>
</tr>
</thead>
<tbody>
<tr>
<td>AAA</td>
<td>99.36</td>
<td>0.53</td>
<td>0.05</td>
<td>0.04</td>
<td>0.02</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>AA</td>
<td>0.39</td>
<td>98.31</td>
<td>1.26</td>
<td>0.01</td>
<td>0.03</td>
<td>0.01</td>
<td>0.00</td>
</tr>
<tr>
<td>A</td>
<td>-0.02</td>
<td>1.65</td>
<td>97.14</td>
<td>1.21</td>
<td>0.02</td>
<td>0.01</td>
<td>0.00</td>
</tr>
<tr>
<td>BBB</td>
<td>0.01</td>
<td>-0.07</td>
<td>2.28</td>
<td>96.72</td>
<td>1.06</td>
<td>-0.01</td>
<td>0.01</td>
</tr>
<tr>
<td>BB</td>
<td>0.00</td>
<td>0.02</td>
<td>-0.12</td>
<td>2.29</td>
<td>96.92</td>
<td>0.88</td>
<td>0.01</td>
</tr>
<tr>
<td>B</td>
<td>0.00</td>
<td>0.00</td>
<td>0.04</td>
<td>-0.15</td>
<td>2.45</td>
<td>97.42</td>
<td>0.25</td>
</tr>
<tr>
<td>CCC</td>
<td>0.00</td>
<td>0.00</td>
<td>0.02</td>
<td>0.04</td>
<td>0.05</td>
<td>1.37</td>
<td>98.53</td>
</tr>
</tbody>
</table>

Remark 25 Another approach to analyze the two rating systems is to compute the monthly transition matrix associated to the migration matrix #1. In this case, we have to find the matrix $M$ such
that \( M^{(12)} = P \). The solution\(^{67}\) is given by \( M = P^{1/12} \) and reported in Table 2.25. We can compare it with the matrix in Table 2.23. Because \( M \) has some negative probabilities, it is not a transition matrix, which indicates that the rating system \#1 does not satisfy the Markov property\(^{68}\).

Box 2.7: Mean hitting time

Let \( \mathcal{A} \subset \mathcal{K} \) be a given subset. The first hitting time of \( \mathcal{A} \) is given by:

\[
T(\mathcal{A}) = \inf \{ n : R(n) \in \mathcal{A} \}
\]

\( T(\mathcal{A}) \) measures how long it takes to reach the target states \( j \in \mathcal{A} \). We can show that it is a stopping time. The mean first hitting (or passage) time to target \( \mathcal{A} \) from state \( k \) is defined as:

\[
\tau_k(\mathcal{A}) = \mathbb{E}[T(\mathcal{A}) | R(0) = R_k]
\]

Let \( \boldsymbol{\tau}(\mathcal{A}) = (\tau_1(\mathcal{A}), \ldots, \tau_K(\mathcal{A})) \) be the vector of mean first hitting times. Norris (1997) showed that:

\[
\tau_k(\mathcal{A}) = 1 + \sum_{j=1}^K p_{k,j} \tau_j(\mathcal{A})
\]

By construction, we have \( \tau_k(\mathcal{A}) = 0 \) if \( k \in \mathcal{A} \). In fact, \( \tau_k(\mathcal{A}) \) is the minimal non negative solution to the previous system. It follows that \( \| \boldsymbol{\tau}(\mathcal{A}) \| = \sum_{k=1}^K |\tau_k(\mathcal{A})| = \sum_{k=1}^K \tau_k(\mathcal{A}) \) because \( \tau_k(\mathcal{A}) \geq 0 \). We deduce that:

\[
\boldsymbol{\tau}(\mathcal{A}) = \arg \min \sum_{k=1}^K x_k
\]

s.t. \( \begin{cases} 
  x_k = 0 & \text{if } k \in \mathcal{A} \\
  x_k = 1 + \sum_{j=1}^K p_{k,j} x_j & \text{if } k \notin \mathcal{A} \\
  x_k \geq 0 & \end{cases} \)

We obtain a linear programming problem with \( K + 1 \) equally constraints and \( K \) lower bounds:

\[
\boldsymbol{\tau}(\mathcal{A}) = \arg \min \sum_{k=1}^K x_k
\]

s.t. \( \begin{cases} 
  x_k = 0 & \text{if } k \in \mathcal{A} \\
  \sum_{j \notin \mathcal{A}} p_{k,j} x_j = -1 \\
  \sum_{j \notin \mathcal{A} \cup \{k\}} p_{k,j} x_j + (p_{k,k} - 1) x_k = -1 & \text{if } k \notin \mathcal{A} \\
  x_k \geq 0 & \end{cases} \)

---

\(^{67}\)Since \( f(x) = x^\alpha \) with \( \alpha > 1 \) is a transcendental function, we use the Schur decomposition \( P = QTQ^* \) to compute numerically the matrix \( M \). Using Appendix A.1.1, we deduce that \( M = QT^{1/12}Q^* \).

\(^{68}\)The Markov property of ESG ratings is discussed later on page 119.
Let $\mathcal{B} = \{\text{AAA, AA, A}\}$ and $\mathcal{W} = \{\text{BB, B, CCC}\}$ be the best-in-class and worst-in-class sets. We obtain the following mean hitting times (in years) for the two rating systems:

<table>
<thead>
<tr>
<th>Rating system</th>
<th>$\mathcal{W}$-target</th>
<th>$\mathcal{B}$-target</th>
</tr>
</thead>
<tbody>
<tr>
<td>AAA</td>
<td>79.21</td>
<td>7.50</td>
</tr>
<tr>
<td>AA</td>
<td>70.04</td>
<td>13.28</td>
</tr>
<tr>
<td>A</td>
<td>62.34</td>
<td>17.58</td>
</tr>
<tr>
<td>BBB</td>
<td>46.54</td>
<td>22.68</td>
</tr>
<tr>
<td>BB</td>
<td>8.68</td>
<td>14.26</td>
</tr>
<tr>
<td>B</td>
<td>11.99</td>
<td>17.54</td>
</tr>
</tbody>
</table>

**Estimation of the transition matrix** Using Bayes theorem, we have:

$$p_{i,j} = \frac{\Pr \{ R(t+1) = R_j | R(t) = R_i \}}{\Pr \{ R(t) = R_i \}}$$

We reiterate that $^69$ $R(t) = R_k \Leftrightarrow S(t) \in [s_{k-1}^*, s_k^*]$. We have seen that:

$$\Pr \{ R(t) = R_k \} = F(s_k^*) - F(s_{k-1}^*) = p_k$$

where $F(s)$ is the probability distribution of the score $S(t)$. We assume that $^70$:

$$\Pr \{ S(t) \leq s, S(t+1) \leq s' \} = C(F(s), F(s'))$$

where $C$ is the copula function of the random vector $(S(t), S(t+1))$. We deduce that:

$$\Pr \{ R(t+1) = R_j, R(t) = R_i \} = \Pr \{ s_{i-1}^* \leq S(t) \leq s_i^*, s_{j-1}^* \leq S(t+1) \leq s_j^* \} = C(F(s_{i-1}^*), F(s_i^*)) - C(F(s_{i-1}^*), F(s_j^*)) - C(F(s_i^*), F(s_{j-1}^*)) + C(F(s_{j-1}^*), F(s_j^*))$$

Finally, we obtain:

$$p_{i,j} = \frac{C(F(s_i^*), F(s_j^*)) - C(F(s_{i-1}^*), F(s_j^*)) - C(F(s_i^*), F(s_{j-1}^*)) + C(F(s_{j-1}^*), F(s_j^*))}{F(s_i^*) - F(s_{i-1}^*)}$$

This is the theoretical expression of the probability transition $p_{i,j}$. In practice, we do not know the probability functions $F$ and $C$. Therefore, we can estimate them and the estimated value of $p_{i,j}$ is equal to:

$$\hat{p}_{i,j} = \frac{\hat{C}(\hat{F}(s_i^*), \hat{F}(s_j^*)) - \hat{C}(\hat{F}(s_{i-1}^*), \hat{F}(s_j^*)) - \hat{C}(\hat{F}(s_i^*), \hat{F}(s_{j-1}^*)) + \hat{C}(\hat{F}(s_{j-1}^*), \hat{F}(s_j^*))}{\hat{F}(s_i^*) - \hat{F}(s_{i-1}^*)}$$

This parametric estimation approach is interesting when we specify the parametric functions $F(s; \theta_1)$ and $C(s, s'; \theta_2)$, and we estimate the parameters $\theta_1$ and $\theta_2$.

Generally, we have no idea about the probability functions $F$ and $C$. We can then adopt a non-parametric estimation approach. The first idea is to replace $F$ and $C$ by the empirical distribution of $S(t)$ and the empirical copula of $(S(t), S(t+1))$. In practice, we can simplify this approach by estimating directly the empirical probability. Thanks to the Bayes theorem, we have:

$$\hat{p}_{i,j}(t) = \frac{\# \{ R(t+1) = R_j, R(t) = R_i \}}{\# \{ R(t) = R_i \}}$$

$^69$ In this analysis, we have the following correspondence: $R_1 = \text{CCC}$, $R_2 = \text{B}$, $\ldots$, $R_K = \text{AAA}$.

$^70$ There is no reason that the probability distribution of $S(t+1)$ is different than that of $S(t)$.
We consider a cohort of issuers for a given period \([t, t + 1]\). Let \(n_i(t)\) be the number of issuers rated \(R_i\) at the beginning of the period \(t\). Let \(n_{i,j}(t)\) be the number of issuers rated \(R_i\) at the beginning of the period \(t\) and \(R_j\) at the end of the period \(t\). We deduce that \(\hat{p}_{i,j}\) is the ration between the two quantities:

\[
\hat{p}_{i,j}(t) = \frac{n_{i,j}(t)}{n_i(t)}
\]

When the period is the year YYYY, the cohort starts on 1 January YYYY and ends on 31 December YYYY. If we have several annual cohorts, we can average the empirical probabilities:

\[
\hat{p}_{i,j} = \frac{1}{T} \sum_{t=1}^{T} \hat{p}_{i,j}(t) = \frac{1}{T} \sum_{t=1}^{T} \frac{n_{i,j}(t)}{n_i(t)}
\]

Another approach is to use the pooling method:

\[
\hat{p}_{i,j} = \frac{\sum_{t=1}^{T} n_{i,j}(t)}{\sum_{t=1}^{T} n_i(t)}
\]

The two approaches give different results. In the first case, each annual cohort has the same weight. In the second case, the approach puts more weight on the year which is more representative.

### Table 2.26: Number of observations \(n_{i,j}\) (migration matrix #1)

<table>
<thead>
<tr>
<th>(n_{i,j})</th>
<th>AAA</th>
<th>AA</th>
<th>A</th>
<th>BBB</th>
<th>BB</th>
<th>B</th>
<th>CCC</th>
<th>(n_i(t))</th>
<th>(\hat{p}_i(t))</th>
</tr>
</thead>
<tbody>
<tr>
<td>AAA</td>
<td>2050</td>
<td>125</td>
<td>20</td>
<td>10</td>
<td>5</td>
<td>0</td>
<td>0</td>
<td>2210</td>
<td>3.683%</td>
</tr>
<tr>
<td>AA</td>
<td>280</td>
<td>5280</td>
<td>800</td>
<td>60</td>
<td>20</td>
<td>5</td>
<td>0</td>
<td>6745</td>
<td>11.242%</td>
</tr>
<tr>
<td>A</td>
<td>20</td>
<td>1700</td>
<td>8020</td>
<td>1150</td>
<td>90</td>
<td>10</td>
<td>0</td>
<td>10990</td>
<td>18.317%</td>
</tr>
<tr>
<td>BBB</td>
<td>10</td>
<td>190</td>
<td>2820</td>
<td>10000</td>
<td>1300</td>
<td>60</td>
<td>10</td>
<td>14390</td>
<td>23.983%</td>
</tr>
<tr>
<td>BB</td>
<td>5</td>
<td>25</td>
<td>200</td>
<td>2500</td>
<td>9150</td>
<td>1000</td>
<td>30</td>
<td>12910</td>
<td>21.517%</td>
</tr>
<tr>
<td>B</td>
<td>0</td>
<td>5</td>
<td>25</td>
<td>150</td>
<td>2260</td>
<td>7800</td>
<td>250</td>
<td>10490</td>
<td>17.483%</td>
</tr>
<tr>
<td>CCC</td>
<td>0</td>
<td>0</td>
<td>5</td>
<td>10</td>
<td>50</td>
<td>300</td>
<td>1900</td>
<td>2265</td>
<td>3.775%</td>
</tr>
<tr>
<td>(\hat{p}_{i,j}(t))</td>
<td>3.942%</td>
<td>12.708%</td>
<td>19.817%</td>
<td>23.133%</td>
<td>21.458%</td>
<td>15.292%</td>
<td>3.650%</td>
<td>100.00%</td>
<td></td>
</tr>
</tbody>
</table>

In Table 2.26, we report all the information for estimating the migration matrix #1. We have used the pooling method with 60,000 observations. For 2,050 observations, the initial rating on 1 January YYYY is AAA and the final rating on 31 December YYYY is AAA. We observe 125 cases where a AAA-rated issuer has been downgraded by one notch. If we compute the sum, we obtain 2,210 AAA-rated observations at the beginning of the year and 2,365 AAA-rated observations at the end of the year. We can then compute the transition probabilities:

\[
\hat{p}_{\text{AAA,AAA}} = \frac{2050}{2210} = 92.76%,
\]

\[
\hat{p}_{\text{CCC,CCC}} = \frac{1900}{2265} = 83.89%.
\]

Previously, we have seen that the stationary distribution of the migration matrix #1 is equal to:

\[
\pi^* = (17.78\%, 29.59\%, 25.12\%, 15.20\%, 8.35\%, 3.29\%, 0.67\%)
\]

---

71From a theoretical viewpoint, this second method is biased. However, it is extensively used in particular when the number of observations is low for each period.

72We have \(n(t) = \sum_{i=1}^{K} n_i(t)\). \(\hat{p}_i(t) = n_i(t)/n(t)\). \(n'(t) = \sum_{j=1}^{K} n_j(t)\). \(\hat{p}_j(t) = n_j(t)/n'(t)\).
In Table 2.26, we observe that the initial empirical distribution of ratings is:

\[ \hat{\pi}^{(0)} = (3.683\%, 11.242\%, 18.317\%, 23.983\%, 21.517\%, 17.483\%, 3.775\%) \]

We conclude that the long-term dynamics of the Markov chain has dramatically change the initial probability distribution. In Table 2.26, we also observe that the final distribution of ratings after one year is:

\[ \hat{\pi}^{(1)} = (3.942\%, 12.708\%, 19.817\%, 23.133\%, 21.458\%, 15.290\%, 3.650\%) \]

We reiterate that the Kolmogorov equation applied to the distribution\(^{73}\) \(\pi^{(n)}\) is given by \(\pi^{(n+1)} = P^T \pi^{(n)}\). In particular, we verify that \(\hat{\pi}^{(1)} = P^T \hat{\pi}^{(0)}\) where \(P = (\hat{p}_{i,j})\). In Figure 2.32, we have reported the dynamics of \(\pi^{(n)}\) with \(\pi^{(0)} = \hat{\pi}^{(0)}\). We conclude that the distribution of the score \(S(t)\) is not stationary.

Figure 2.32: Dynamics of the probability distribution \(\pi^{(n)}\) (migration matrix #1)

Continuous-time modeling

**Markov generator** We now consider the case \(t \in \mathbb{R}_+\). We note \(P(s; t)\) the transition matrix defined as follows:

\[ P_{i,j} (s; t) = p(s; i; t, j) = \Pr \{ R(t) = R_j \mid R(s) = R_i \} \]

Assuming that the Markov chain is time-homogenous, we have \(P(t) = P(0; t)\). Jarrow et al. (1997) introduce the generator matrix \(\Lambda = (\lambda_{i,j})\) where \(\lambda_{i,j} \geq 0\) for all \(i \neq j\) and \(\lambda_{i,i} = -\sum_{j \neq i} K^j \lambda_{i,j}\). In this case, the transition matrix satisfies the following relationship:

\[ P(t) = \exp(t\Lambda) \quad (2.6) \]

\(^{73}\)We have \(\pi^{(n)}_k = \Pr \{ R(n) = R_k \}\).
where \( \exp(A) \) is the matrix exponential of \( A \). Let us give a probabilistic interpretation of \( \Lambda \). If we assume that the probability of jumping from rating \( R_i \) to rating \( R_j \) in a short time period \( \Delta t \) is proportional to \( \Delta t \), we have \( p(t, i; t + \Delta t, j) = \lambda_{i,j} \Delta t \). The matrix form of this equation is \( P(t; t + \Delta t) = \Lambda \Delta t \). We deduce that:

\[
P(t + \Delta t) = P(t) P(t; t + \Delta t) = P(t) \Lambda \Delta t
\]

and:

\[
dP(t) = P(t) \Lambda dt
\]

Because we have \( \exp(0) = I \), we obtain the solution \( P(t) = \exp(t\Lambda) \). We then interpret \( \lambda_{i,j} \) as the instantaneous transition rate of jumping from rating \( R_i \) to rating \( R_j \).

**Remark 26** In Appendix A.1.1, we present the matrix exponential function and its mathematical properties. In particular, we have \( e^{A+B} = e^A e^B \) and \( e^{A(s+t)} = e^{As} e^{At} \) where \( A \) and \( B \) are two square matrices such that \( AB = BA \) and \( s \) and \( t \) are two real numbers.

**Example 8** We consider a rating system with three states: A (good rating), B (average rating) and C (bad rating). The Markov generator is equal to:

\[
\Lambda = \begin{pmatrix}
-0.30 & 0.20 & 0.10 \\
0.15 & -0.40 & 0.25 \\
0.10 & 0.15 & -0.25
\end{pmatrix}
\]

The one-year transition probability matrix is equal to:

\[
P(1) = e^\Lambda = \begin{pmatrix}
75.63\% & 14.84\% & 9.53\% \\
11.63\% & 69.50\% & 18.87\% \\
8.52\% & 11.73\% & 79.75\%
\end{pmatrix}
\]

For the two-year maturity, we get:

\[
P(2) = e^{2\Lambda} = \begin{pmatrix}
59.74\% & 22.65\% & 17.61\% \\
18.49\% & 52.24\% & 29.27\% \\
14.60\% & 18.76\% & 66.63\%
\end{pmatrix}
\]

We verify that \( P(2) = P(1) \cdot P(1) \). This derives from the property of the matrix exponential:

\[
P(t) = e^{t\Lambda} = (e^\Lambda)^t = P(1)^t
\]

The continuous-time framework allows to calculate transition matrices for non-integer maturities, which do not correspond to full years. For instance, the one-month transition probability matrix of the previous example is equal to:

\[
P\left(\frac{1}{12}\right) = e^{\frac{1}{12}\Lambda} = \begin{pmatrix}
97.54\% & 1.62\% & 0.83 \\
1.22\% & 96.74\% & 2.03 \\
0.82\% & 1.22\% & 97.95
\end{pmatrix}
\]
Box 2.8: Estimation of the Markov generator

One of the issues with the continuous-time framework is to estimate the Markov generator \( \hat{\Lambda} \). One solution consists in using the empirical transition matrix \( \hat{P} (t) \), which have been calculated for a given time horizon \( t \). In this case, the estimate \( \hat{\Lambda} \) must satisfy the relationship \( \hat{P} (t) = \exp \left( t \hat{\Lambda} \right) \). We deduce that:

\[
\hat{\Lambda} = \frac{1}{t} \ln \left( \hat{P} (t) \right)
\]

where \( \ln A \) is the matrix logarithm of \( A \). However, the matrix \( \hat{\Lambda} \) cannot verify the Markov conditions \( \hat{\lambda}_{i,j} \geq 0 \) for all \( i \neq j \) and \( \sum_{j=1}^{K} \hat{\lambda}_{i,j} = 0 \). Therefore, Israel et al. (2001) propose two estimators to obtain a valid generator:

1. the first approach consists in adding the negative values back into the diagonal values:

\[
\begin{align*}
\tilde{\lambda}_{i,j} &= \max \left( \hat{\lambda}_{i,j}, 0 \right) \quad i \neq j \\
\tilde{\lambda}_{i,i} &= \hat{\lambda}_{i,i} + \sum_{j \neq i} \min \left( \hat{\lambda}_{i,j}, 0 \right)
\end{align*}
\]

2. in the second method, we carry forward the negative values on the matrix entries which have the correct sign:

\[
\begin{align*}
G_i &= \left| \hat{\lambda}_{i,i} \right| + \sum_{j \neq i} \max \left( \hat{\lambda}_{i,j}, 0 \right) \\
B_i &= \sum_{j \neq i} \max \left( -\hat{\lambda}_{i,j}, 0 \right) \\
\hat{\lambda}_{i,j} &= \begin{cases} \\
0 & \text{if } i \neq j \text{ and } \hat{\lambda}_{i,j} < 0 \\
\hat{\lambda}_{i,j} - B_i \left| \hat{\lambda}_{i,j} \right| / G_i & \text{if } G_i > 0 \\
\hat{\lambda}_{i,j} & \text{if } G_i = 0
\end{cases}
\end{align*}
\]

Markov property The Markov property refers to the lack of memory of stochastic processes. This implies that the probability distribution of future states of the process conditional on both past and present values depends only upon the present state. Therefore, given the present, the future does not depend on the past. In order to better understand the implications of this property, we consider the following example with three companies:

<table>
<thead>
<tr>
<th></th>
<th>( t-2 )</th>
<th>( t-1 )</th>
<th>( t )</th>
<th>( t+1 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>AAA</td>
<td>BBB</td>
<td>BBB</td>
<td>BBB</td>
<td>?</td>
</tr>
<tr>
<td>BBB</td>
<td>BBB</td>
<td>BBB</td>
<td>BBB</td>
<td>?</td>
</tr>
<tr>
<td>BB</td>
<td>BB</td>
<td>BBB</td>
<td>BBB</td>
<td>?</td>
</tr>
</tbody>
</table>

Today, the three companies are rated BBB. We would like to predict the ESG rating of those companies at time \( t+1 \). If the ESG ratings are Markovian, these entities are equivalent and have the same conditional probabilities to become AAA, AA, etc. Otherwise, this means that the conditional probabilities depend on the past trajectory. In this case, we have:

\[
\Pr \{ R_{c_1} (t+1) = R_j \mid R_{c_1} (t) = R_i \} \neq \Pr \{ R_{c_2} (t+1) = R_j \mid R_{c_2} (t) = R_i \}
\]

for two different companies \( c_1 \) and \( c_2 \). In our example, the firms have different past trajectories. They don’t have the same transition matrix if the rating process has not the Markov property.
To verify the Markov property, we compute the matrix $\Lambda' = \ln(P)$ and measure whether $\Lambda'$ is a Markov generator or not. Using the rating migration matrix #1, we obtain the results given in Table 2.27. We notice that $\ln P$ is not a Markov generator since 11 off-diagonal elements are not positive. Using the first method of Israel et al. (2001) described in Box 2.8, we transform this matrix into a Markov generator\(^\text{74}\) $\Lambda$ (Table 2.28). We recompute the one-year transition matrix $\bar{P}(1) = \exp(\bar{\Lambda})$ and observe some small differences with the original transition matrix (see Table 2.29 vs. Table 2.20).

Table 2.27: Non-Markov generator $\Lambda' = \ln(P)$ of the migration matrix #1 (in %)

<table>
<thead>
<tr>
<th></th>
<th>AAA</th>
<th>AA</th>
<th>A</th>
<th>BBB</th>
<th>BB</th>
<th>B</th>
<th>CCC</th>
</tr>
</thead>
<tbody>
<tr>
<td>AAA</td>
<td>-7.663</td>
<td>6.427</td>
<td>0.542</td>
<td>0.466</td>
<td>0.245</td>
<td>-0.016</td>
<td>-0.000</td>
</tr>
<tr>
<td>AA</td>
<td>4.770</td>
<td>-20.604</td>
<td>15.451</td>
<td>-0.001</td>
<td>0.318</td>
<td>0.066</td>
<td>-0.001</td>
</tr>
<tr>
<td>A</td>
<td>-0.267</td>
<td>20.259</td>
<td>-35.172</td>
<td>14.953</td>
<td>0.152</td>
<td>0.083</td>
<td>-0.008</td>
</tr>
<tr>
<td>BBB</td>
<td>0.102</td>
<td>-1.051</td>
<td>28.263</td>
<td>-40.366</td>
<td>13.100</td>
<td>-0.128</td>
<td>0.080</td>
</tr>
<tr>
<td>BB</td>
<td>0.032</td>
<td>0.307</td>
<td>-1.762</td>
<td>28.351</td>
<td>-37.889</td>
<td>10.832</td>
<td>0.129</td>
</tr>
<tr>
<td>B</td>
<td>-0.005</td>
<td>-0.008</td>
<td>0.503</td>
<td>-2.240</td>
<td>30.227</td>
<td>-31.482</td>
<td>3.006</td>
</tr>
<tr>
<td>CCC</td>
<td>0.000</td>
<td>-0.024</td>
<td>0.194</td>
<td>0.469</td>
<td>0.365</td>
<td>16.806</td>
<td>-17.810</td>
</tr>
</tbody>
</table>

Table 2.28: Markov generator of the migration matrix #1 (in %)

<table>
<thead>
<tr>
<th></th>
<th>AAA</th>
<th>AA</th>
<th>A</th>
<th>BBB</th>
<th>BB</th>
<th>B</th>
<th>CCC</th>
</tr>
</thead>
<tbody>
<tr>
<td>AAA</td>
<td>-7.679</td>
<td>6.427</td>
<td>0.542</td>
<td>0.466</td>
<td>0.245</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>AA</td>
<td>4.770</td>
<td>-20.606</td>
<td>15.451</td>
<td>0.000</td>
<td>0.318</td>
<td>0.066</td>
<td>0.000</td>
</tr>
<tr>
<td>A</td>
<td>0.000</td>
<td>20.259</td>
<td>-35.447</td>
<td>14.953</td>
<td>0.152</td>
<td>0.083</td>
<td>0.000</td>
</tr>
<tr>
<td>BBB</td>
<td>0.102</td>
<td>0.000</td>
<td>28.263</td>
<td>-41.545</td>
<td>13.100</td>
<td>0.000</td>
<td>0.080</td>
</tr>
<tr>
<td>BB</td>
<td>0.032</td>
<td>0.307</td>
<td>0.000</td>
<td>38.351</td>
<td>-39.651</td>
<td>10.832</td>
<td>0.129</td>
</tr>
<tr>
<td>B</td>
<td>0.000</td>
<td>0.000</td>
<td>0.503</td>
<td>0.000</td>
<td>30.227</td>
<td>-33.735</td>
<td>3.006</td>
</tr>
<tr>
<td>CCC</td>
<td>0.000</td>
<td>0.000</td>
<td>0.194</td>
<td>0.469</td>
<td>0.365</td>
<td>16.806</td>
<td>-17.834</td>
</tr>
</tbody>
</table>

Table 2.29: ESG migration Markov matrix #1 (one-year transition probability in %)

<table>
<thead>
<tr>
<th></th>
<th>AAA</th>
<th>AA</th>
<th>A</th>
<th>BBB</th>
<th>BB</th>
<th>B</th>
<th>CCC</th>
</tr>
</thead>
<tbody>
<tr>
<td>AAA</td>
<td>92.75</td>
<td>5.66</td>
<td>0.90</td>
<td>0.45</td>
<td>0.23</td>
<td>0.01</td>
<td>0.00</td>
</tr>
<tr>
<td>AA</td>
<td>4.17</td>
<td>82.73</td>
<td>11.85</td>
<td>0.89</td>
<td>0.30</td>
<td>0.07</td>
<td>0.00</td>
</tr>
<tr>
<td>A</td>
<td>0.40</td>
<td>15.51</td>
<td>72.79</td>
<td>10.39</td>
<td>0.81</td>
<td>0.10</td>
<td>0.01</td>
</tr>
<tr>
<td>BBB</td>
<td>0.12</td>
<td>2.11</td>
<td>19.60</td>
<td>68.69</td>
<td>8.91</td>
<td>0.50</td>
<td>0.07</td>
</tr>
<tr>
<td>BB</td>
<td>0.04</td>
<td>0.43</td>
<td>2.79</td>
<td>19.25</td>
<td>69.65</td>
<td>7.61</td>
<td>0.23</td>
</tr>
<tr>
<td>B</td>
<td>0.01</td>
<td>0.09</td>
<td>0.65</td>
<td>2.98</td>
<td>21.21</td>
<td>72.71</td>
<td>2.35</td>
</tr>
<tr>
<td>CCC</td>
<td>0.00</td>
<td>0.02</td>
<td>0.25</td>
<td>0.58</td>
<td>2.19</td>
<td>13.09</td>
<td>83.87</td>
</tr>
</tbody>
</table>

\(^{74}\)The matrix $\Lambda$ is the best Markov generator that minimize the $L_1$-norm distance to $P$. 

*Handbook of Sustainable Finance*
Dynamic analysis We have now all the tools to conduct a dynamic analysis of the ESG rating system. There is tremendous potential. For instance, we compute the probability to reach the states $\mathcal{A}$ with the following formula:

$$
\pi_k(t, \mathcal{A}) = \Pr \{ R(t) \in \mathcal{A} \mid R(0) = k \} = \sum_{j \in \mathcal{A}} e_k^T e^t \Lambda e_j^T
$$

Some examples are given in Figure 2.33. We can also use the continuous-time framework to investigate the probability density function of conditional events, the probability over a given interval, the $m$-order derivative of time functions, etc. We use the properties $\partial_t \Lambda \exp(\Lambda t) = \Lambda \exp(\Lambda t)$, $\partial_t^m \exp(\Lambda t) = \Lambda^m \exp(\Lambda t)$ and $\int_0^t e^{\Lambda s} \, ds = (e^{\Lambda t} - I_K) \Lambda^{-1}$. For example, we have:

$$
\pi_k^{(m)}(t, \mathcal{A}) := \frac{\partial \pi_k(t, \mathcal{A})}{\partial t^m} = \sum_{j \in \mathcal{A}} e_k^T \Lambda^m \Lambda e_j^T
$$

$\pi_k^{(1)}(t, \mathcal{A})$ may be interpreted as a “time density function”. In Figure 2.33, we report $\pi_k(t, \text{AAA})$, $\pi_k^{(1)}(t, \text{AAA})$, $\pi_k(t, \text{CCC})$ and $\pi_k^{(1)}(t, \text{CCC})$. We observe the strange behavior of the CCC rating towards the AAA rating.

Figure 2.33: Probability $\pi_k(t, \mathcal{A})$ to reach $\mathcal{A}$ at time $t$ (migration matrix #1)

Remark 27 The previous analysis can be used to check consistency of ratings. In particular, the fact that ratings satisfy ordering preferences implies that we must generally observe a monotone behavior of quantities that are a non-decreasing and concave function of ratings.

\[^{75}\text{For more general integrals of type } \int_0^t e^{\Lambda s} Q f(s) \, ds, \text{ we use the numerical algorithms developed by Van Loan (1978).}\]
Figure 2.34: Time functions $\pi_k(t, \text{AAA})$, $\pi_k^{(1)}(t, \text{AAA})$, $\pi_k(t, \text{CCC})$ and $\pi_k^{(1)}(t, \text{CCC})$ (migration matrix #1)

Box 2.9: Computing statistical moments with continuous-time Markov chains

The distribution $\pi(t)$ follows the Kolmogorov equation:

$$\frac{d\pi(t)}{dt} = \Lambda \pi(t)$$

It follows that $\pi(t) = e^{\Lambda t} \pi(0)$. Let $Y(t) = \phi(\mathcal{R}(t))$ be a random variable that depends on the ratings. We have:

$$\mu(t) = \sum_{k=1}^{K} \phi(R_k) \pi_k(t)$$

and:

$$\sigma^2(t) = \sum_{k=1}^{K} (\phi(R_k) - \mu(t))^2 \pi_k(t)$$
2.3.4 Comparison with credit ratings

The modeling of credit ratings is similar than this of ESG ratings, but there is one important difference. The states include the default state. This means that \( R_K \) is the absorbing state, implying that any entity which has reached this state remains in this state. In this case, \( p_{i,K} \) is the one-period default probability of rating \( R_i \) and we have \( p_{i,K} = 1 \). An example of credit migration matrix is given in Table 2.30. It is the S&P one-year transition probability matrix for corporate bonds estimated by Kavvathas (2001) for the period 1960-1998. More recent credit migration matrices are given in Table 2.31.

### Table 2.30: Example of credit migration matrix (one-year probability transition in %)

<table>
<thead>
<tr>
<th></th>
<th>AAA</th>
<th>AA</th>
<th>A</th>
<th>BBB</th>
<th>BB</th>
<th>B</th>
<th>CCC</th>
<th>D</th>
</tr>
</thead>
<tbody>
<tr>
<td>AAA</td>
<td>92.82</td>
<td>6.50</td>
<td>0.56</td>
<td>0.06</td>
<td>0.06</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>AA</td>
<td>0.63</td>
<td>91.87</td>
<td>6.64</td>
<td>0.65</td>
<td>0.06</td>
<td>0.11</td>
<td>0.04</td>
<td>0.00</td>
</tr>
<tr>
<td>A</td>
<td>0.08</td>
<td>2.26</td>
<td>91.66</td>
<td>5.11</td>
<td>0.61</td>
<td>0.23</td>
<td>0.01</td>
<td>0.04</td>
</tr>
<tr>
<td>BBB</td>
<td>0.05</td>
<td>0.27</td>
<td>5.84</td>
<td>87.74</td>
<td>4.74</td>
<td>0.98</td>
<td>0.16</td>
<td>0.22</td>
</tr>
<tr>
<td>BB</td>
<td>0.04</td>
<td>0.11</td>
<td>0.64</td>
<td>7.85</td>
<td>81.14</td>
<td>8.27</td>
<td>0.89</td>
<td>1.06</td>
</tr>
<tr>
<td>B</td>
<td>0.00</td>
<td>0.11</td>
<td>0.30</td>
<td>0.42</td>
<td>6.75</td>
<td>83.07</td>
<td>3.86</td>
<td>5.49</td>
</tr>
<tr>
<td>CCC</td>
<td>0.19</td>
<td>0.00</td>
<td>0.38</td>
<td>0.75</td>
<td>2.44</td>
<td>12.03</td>
<td>60.71</td>
<td>23.50</td>
</tr>
<tr>
<td>D</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>100.00</td>
<td></td>
</tr>
</tbody>
</table>


### Table 2.31: Credit migration matrix in % (Moody’s, 1983-2021)

<table>
<thead>
<tr>
<th></th>
<th>Aaa</th>
<th>Aa</th>
<th>A</th>
<th>Baa</th>
<th>Ba</th>
<th>B</th>
<th>Caa</th>
<th>W</th>
<th>D</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sovereign issuers</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Aaa</td>
<td>96.99</td>
<td>2.87</td>
<td>0.03</td>
<td>0.08</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.03</td>
<td>0.00</td>
</tr>
<tr>
<td>Aa</td>
<td>2.73</td>
<td>93.52</td>
<td>2.56</td>
<td>0.62</td>
<td>0.09</td>
<td>0.00</td>
<td>0.00</td>
<td>0.47</td>
<td>0.00</td>
</tr>
<tr>
<td>A</td>
<td>0.00</td>
<td>3.60</td>
<td>92.17</td>
<td>3.19</td>
<td>0.98</td>
<td>0.06</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Baa</td>
<td>0.00</td>
<td>0.00</td>
<td>5.43</td>
<td>89.17</td>
<td>4.98</td>
<td>0.39</td>
<td>0.03</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Ba</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>6.91</td>
<td>85.72</td>
<td>6.53</td>
<td>0.29</td>
<td>0.10</td>
<td>0.44</td>
</tr>
<tr>
<td>B</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>4.31</td>
<td>88.49</td>
<td>4.50</td>
<td>0.26</td>
<td>2.43</td>
</tr>
<tr>
<td>Caa</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.06</td>
<td>13.60</td>
<td>73.24</td>
<td>0.75</td>
<td>12.35</td>
</tr>
<tr>
<td>Corporates issuers</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Aaa</td>
<td>87.16</td>
<td>8.05</td>
<td>0.45</td>
<td>0.08</td>
<td>0.03</td>
<td>0.00</td>
<td>0.00</td>
<td>4.23</td>
<td>0.00</td>
</tr>
<tr>
<td>Aa</td>
<td>0.70</td>
<td>85.02</td>
<td>8.57</td>
<td>0.42</td>
<td>0.06</td>
<td>0.04</td>
<td>0.02</td>
<td>5.17</td>
<td>0.02</td>
</tr>
<tr>
<td>A</td>
<td>0.05</td>
<td>2.44</td>
<td>86.84</td>
<td>5.15</td>
<td>0.45</td>
<td>0.10</td>
<td>0.04</td>
<td>4.88</td>
<td>0.05</td>
</tr>
<tr>
<td>Baa</td>
<td>0.02</td>
<td>0.12</td>
<td>3.73</td>
<td>86.43</td>
<td>3.42</td>
<td>0.65</td>
<td>0.16</td>
<td>5.31</td>
<td>0.15</td>
</tr>
<tr>
<td>Ba</td>
<td>0.00</td>
<td>0.03</td>
<td>0.38</td>
<td>6.02</td>
<td>75.95</td>
<td>7.19</td>
<td>0.86</td>
<td>8.78</td>
<td>0.77</td>
</tr>
<tr>
<td>B</td>
<td>0.01</td>
<td>0.03</td>
<td>0.12</td>
<td>0.42</td>
<td>4.73</td>
<td>73.61</td>
<td>7.34</td>
<td>10.79</td>
<td>2.95</td>
</tr>
<tr>
<td>Caa</td>
<td>0.00</td>
<td>0.01</td>
<td>0.02</td>
<td>0.07</td>
<td>0.26</td>
<td>5.58</td>
<td>70.41</td>
<td>14.82</td>
<td>8.83</td>
</tr>
</tbody>
</table>

Source: Moody’s (2020).

\(^{76}W\) means that the issuer has required to stop the rating (withdrawn).
Since there are few research on ESG ratings, credit migration matrices can be used as a benchmark to compare the two rating systems. For that, we consider the trace statistics:

$$\lambda(t) = \frac{\text{trace}(e^{t\Lambda})}{K}$$

It is the average of the diagonal transition probabilities. It measures the average probability to remain in its state\(^{77}\). Results are reported in Figure 2.35. Even if the two ESG rating systems used here are fictitious examples, we generally conclude that ESG rating systems are less stable than credit rating systems, and the time horizon of ESG ratings for prediction is shorter.

**Figure 2.35**: Trace statistics of credit and ESG migration matrices

\(^{77}\)For a credit migration matrix, we consider all the states except the absorbing state. In this case, we have $$\lim_{t \to \infty} \lambda(t) = 0$$.
(a) Let \( s \in [0, 1] \). Find the points of intersection between the curve \( x_2 = (s - \omega X_1) / (1 - \omega) \) and the unit square. Discuss the different cases.

(b) For each case, compute the area \( \mathcal{A}(s) \) defined as:

\[
\mathcal{A}(s) = \iint_{\Omega(s)} dx_1 \, dx_2
\]

where \( \Omega(s) = \{(x_1, x_2) \in [0, 1]^2 : \omega x_1 + (1 - \omega) x_2 \leq s\} \). Deduce the cumulative distribution function \( G \) of the score.

(c) Compute the density function \( g \).

(d) Find \( G \) and \( g \) when \( X_j \sim U_{[a,b]} \) where \( b > a \).

2. We consider the case \( m = 3 \) and \( X_j \sim U_{[0,1]} \). The volume \( \mathcal{V}(s) \) is equal to:

\[
\mathcal{V}(s) = \iiint_{\Omega(s)} dx_1 \, dx_2 \, dx_3
\]

where \( \Omega(s) = \{(x_1, x_2, x_3) \in [0, 1]^3 : x_1 + x_2 + x_3 \leq s\} \).

(a) Compute the volume \( \mathcal{V}(s) \) when \( 0 \leq s \leq 1 \).

(b) Compute the volume difference \( \mathcal{V}(s) - \mathcal{V}(1) \) when \( 1 \leq s \leq 2 \).

(c) Compute the volume difference \( \mathcal{V}(s) - \mathcal{V}(2) \) when \( 1 \leq s \leq 2 \).

(d) Deduce the cumulative distribution function \( G \) of the score.

(e) Compute the density function \( g \).

3. We consider that \( X_j \sim U_{[0,1]} \) and \( m \geq 1 \). We note \( G_m(s) \) the probability \( \Pr \{S \leq s\} \).

(a) Give the expression of \( G_m(s) \) and the associate density function \( g_m(s) \).

(b) We assume that \( X_j \sim U_{[a,b]} \) where \( b > a \). Deduce the expressions of the density and distribution functions of the score \( S \).

4. We assume that \( X_j \sim \mathcal{G}(\alpha_j, \beta) \) where \( \alpha_j > 0 \) and \( \beta > 0 \).

(a) Compute the cumulative distribution function \( G \) of the score.

(b) Deduce the density function \( g \).

(c) Compute the mean and the variance of \( S \).

(d) We assume that \( \alpha_j = 2 \) and \( \beta = 2 \).

i. Draw the functions \( \mathbb{E}[S] \) and \( \text{var}(S) \) with respect to the number \( m \) of features.

ii. Find the value \( m^+(p, \varepsilon) \) such that:

\[
m^+(p, \varepsilon) = \inf \{m : \Pr \{2 - \varepsilon \leq S \leq 2 - \varepsilon \} \leq p\}
\]

for the pairs \((p, \varepsilon) = (99\%, 5\%)\).

iii. Draw the function \( m^+(p, \varepsilon) \) with respect to \( p \) when \( \varepsilon = 1\% \).

iv. Draw the function \( m^+(p, \varepsilon) \) with respect to \( \varepsilon \) when \( p = 99.99\% \).

---

*Handbook of Sustainable Finance*
2.4.2 Score normalization when the features are correlated

2.4.3 Construction of a sovereign ESG score

2.4.4 Probability distribution of an ESG score

1. We consider an investment universe of 8 issuers with the following ESG scores:

<table>
<thead>
<tr>
<th>Issuer</th>
<th>#1</th>
<th>#2</th>
<th>#3</th>
<th>#4</th>
<th>#5</th>
<th>#6</th>
<th>#7</th>
<th>#8</th>
</tr>
</thead>
<tbody>
<tr>
<td>E</td>
<td>−2.80</td>
<td>−1.80</td>
<td>−1.75</td>
<td>0.60</td>
<td>0.75</td>
<td>1.30</td>
<td>1.90</td>
<td>2.70</td>
</tr>
<tr>
<td>S</td>
<td>−1.70</td>
<td>−1.90</td>
<td>0.75</td>
<td>−1.60</td>
<td>1.85</td>
<td>1.05</td>
<td>0.90</td>
<td>0.70</td>
</tr>
<tr>
<td>G</td>
<td>0.30</td>
<td>−0.70</td>
<td>−2.75</td>
<td>2.60</td>
<td>0.45</td>
<td>2.35</td>
<td>2.20</td>
<td>1.70</td>
</tr>
</tbody>
</table>

(a) Calculate the ESG score of the issuers if we assume the following weighting scheme: 40% for E, 40% for S, and 20% for G.

(b) Calculate the ESG score of the equally-weighted portfolio \( x_{\text{ew}} \).

2. We assume that the ESG scores are iid and follow a standard Gaussian distribution: \( S_i \sim N(0,1) \)

(a) We note \( x_{\text{ew}}^{(n)} \) the equally-weighted portfolio composed of \( n \) issuers. Calculate the distribution of the ESG score \( S \left( x_{\text{ew}}^{(n)} \right) \) of the portfolio \( x_{\text{ew}}^{(n)} \).

(b) What is the ESG score of a well-diversified portfolio?

(c) We note \( T \sim F_\alpha \) where \( F_\alpha (t) = t^\alpha, t \in [0,1] \) and \( \alpha \geq 0 \). Draw the graph of the probability density function \( f_\alpha (t) \) when \( \alpha \) is respectively equal to 0.5, 1.5, 2.5 and 70. What do you notice?

(d) We assume that the weights of the portfolio \( x = (x_1, \ldots, x_n) \) follow a power-law distribution \( F_\alpha \):

\[
x_i \sim c T_i
\]

where \( T_i \sim F_\alpha \) are iid random variables and \( c \) is a normalization constant. Explain how to simulate the portfolio weights \( x = (x_1, \ldots, x_n) \). Represent one simulation of the portfolio \( x \) for the previous values of \( \alpha \). Comment on these results. Deducethe relationship between the Herfindahl index \( H_\alpha (x) \) of the portfolio weights \( x \) and the parameter \( \alpha \).

(e) We assume that the weight \( x_i \) and the ESG score \( S_i \) of the issuer \( i \) are independent. How to simulate the portfolio’s score \( S (x) \)? Using 50 000 replications, estimate the probability distribution function of \( S (x) \) by the Monte Carlo method. Comment on these results.

(f) We now assume that the weight \( x_i \) and the ESG score \( S_i \) of the issuer \( i \) are positively correlated. More precisely, the dependence function between \( x_i \) and \( S_i \) is the Normal copula function with parameter \( \rho \). Show that this is also the copula function between \( T_i \) and \( S_i \). Deduce an algorithm to simulate \( S (x) \).

(g) Using 50 000 replications, estimate the probability distribution function of \( S (x) \) by the Monte Carlo method when the correlation parameter \( \rho \) is set to 50%. Comment on these results.

(h) Estimate the relationship between the correlation parameter \( \rho \) and the expected ESG score \( \mathbb{E} [S (x)] \) of the portfolio \( x \). Comment on these results.

\( ^{78} \) We use \( n = 50 \) in the rest of the exercise.
(i) How are the previous results related to the size bias of ESG scoring?

3. Let $S$ be the ESG score of the issuer. We assume that the ESG score follows a standard Gaussian distribution:

$$S \sim \mathcal{N}(0, 1)$$

The ESG score $S$ is also converted into an ESG rating $R$, which can take the values $A$, $B$, $C$ and $D$.

(a) We assume that the breakpoints of the rating system are $-1.5$, $0$ and $+1.5$. Compute the frequencies of the ratings.

(b) We would like to build a rating system such that each category has the same frequency. Find the mapping function.

(c) We would like to build a rating system such that the frequency of the median ratings $B$ and $C$ is $40\%$ and the frequency of the extreme ratings $A$ and $D$ is $10\%$. Find the mapping function.

4. Let $S(t)$ be the ESG score of the issuer at time $t$. The ESG scoring system is evaluated every month. The index time $t$ corresponds to the current month, whereas the previous month is $t-1$. We assume that:

(a) i. The ESG score at time $t-1$ follows a standard Gaussian distribution:

$$S(t-1) \sim \mathcal{N}(0, 1)$$

ii. The variation of the ESG score is Gaussian between two months:

$$\Delta S(t) = S(t) - S(t-1) \sim \mathcal{N}(0, \sigma^2)$$

iii. The ESG score $S(t-1)$ and the variation $\Delta S(t)$ are independent.

The ESG score $S(t)$ is converted into an ESG rating $R(t)$, which can take following grades:

$$R_1 \prec R_2 \prec \cdots \prec R_k \prec \cdots \prec R_{K-1} \prec R_K$$

We assume that the breakpoints of the rating system are $(s_1, s_2, \ldots, s_{K-1})$. We also note $s_0 = -\infty$ and $s_K = +\infty$.

(a) Compute the bivariate probability distribution of the random vector $(S(t-1), \Delta S(t))$.

(b) Compute the bivariate distribution of the random vector $(S(t-1), S(t))$.

(c) Compute the probability $p_k = \Pr\{R(t-1) = R_k\}$.

(d) Compute the joint probability $\Pr\{R(t) = R_k, R(t-1) = R_j\}$.

(e) Compute the transition probability $p_{j,k} = \Pr\{R(t) = R_k | R(t-1) = R_j\}$.

(f) Compute the monthly turnover $T(R_k)$ of the ESG rating $R_k$.

(g) Compute the monthly turnover $T(R_1, \ldots, R_K)$ of the ESG rating system.

(h) For each rating system given in Questions 3.a, 3.b and 3.c, compute the corresponding migration matrix and the monthly turnover of the rating system if we assume that $\sigma$ is equal to $10\%$. What is the best ESG rating system if we would like to control the turnover of ESG ratings?

---

79 $A$ is the best rating and $D$ is the worst rating.
(i) Draw the relationship between the parameter $\sigma$ and the turnover $T(R_1, \ldots, R_K)$ for the three ESG rating systems.

(j) We consider a uniform ESG rating system where:

$$\Pr\{R(t-1) = R_k\} = \frac{1}{K}$$

Draw the relationship between the number of notches $K$ and the turnover $T(R_1, \ldots, R_K)$ when the parameter $\sigma$ takes the values 5%, 10% and 25%.

(k) Why is an ESG rating system different than a credit rating system? What do you conclude from the previous analysis? What is the issue of ESG exclusion policy and negative screening?

2.4.5 Markov generator of ESG migration matrix

2.4.6 Properties of Markov chains
Chapter 3

Impact of ESG Investing on Asset Prices and Portfolio Returns

The question of the ESG performance is on everyone’s lips. This question is related to several other issues that can be summarized as follows: What is the impact of ESG on corporate financial performance? What is the impact of ESG investing on risk premia? What is the impact of ESG screening on portfolio returns? Is there a difference between ESG investing and climate investing? In fact, we can multiply the questions because the term ESG performance covers different topics, and we must be more precise when we speak about it. First, we must distinguish operational performance, social performance, accounting-based performance, market performance, etc. For instance, it is not the same thing if the assessment is based on financial statements (balance sheet and income statement) or the evolution of the share price. Second, we can measure the performance from the investor or issuer viewpoint. The third vagueness concerns the type of financial assets. Does it concern stocks or bonds? Because we know that fixed-income and equity markets react differently. Another importance source of discrepancy is the choice of financial instruments. We can compare the performance of securities, mutual funds, asset owners or backtests. For example, simulated performance must be different than live performance. The fifth issue is the investment universe and the sample. We may imagine that the impact of ESG is different from one region to another, one sector to another, one period to another, etc. Finally, if we focus on the financial performance of ESG strategies, the last issue is the implementation of the portfolio strategy. Do we speak about an exclusion, selection, integration or momentum strategy? Do we speak about active or passive management? Moreover, as ESG scores highly differ from one rating agency to another rating agency, we are not sure to capture the performance of the ESG market, but perhaps some idiosyncratic patterns. Therefore, there are many factors to take into account, and it is no coincidence that there are plenty of academic studies with divergent conclusions. It is impossible to cite all of them, even the most famous research. They are described in meta-analysis, e.g., Orlitzky et al. (2003), Margolis et al. (2009), Friede et al. (2015), Atz et al. (2022) and Coqueret (2022). Instead of a deep dive on all these empirical studies, we adopt another approach. Indeed, ESG investing did not exist or was so marginal fifteen or twenty years ago. Moreover, ESG data are certainly not robust or relevant before 2010. Therefore, it is better to focus on the theoretical research when analyzing the performance of ESG investing. This first section is mainly based on the works of Pástor et al. (2021) and Pedersen et al. (2021). It will help us to understand when, where and why ESG investing may underperform or overperform business as usual investing. The second section is dedicated to empirical studies, but we make a selection in order to illustrate the theoretical results and concepts defined in the first section. Finally, the question of strategic asset allocation is investigated in the third section.
3.1 Theoretical models

Before discussing the impact of ESG on the theory of risk premium and security selection, we summarize the main results of the modern portfolio theory as presented in Roncalli (2013).

3.1.1 A primer on modern portfolio theory

The concept of the market portfolio has a long history and dates back to the seminal work of Markowitz (1952). He showed that an efficient portfolio is the portfolio that maximizes the expected return for a given level of risk. Markowitz concluded that there is not only one optimal portfolio, but a set of optimal portfolios which is called the efficient frontier. By studying the liquidity preference, Tobin (1958) showed that the efficient frontier becomes a straight line in the presence of a risk-free asset. In this case, optimal portfolios correspond to a combination of the risk-free asset and one particular efficient portfolio named the tangency portfolio. Sharpe (1964) summarized the results of Markowitz and Tobin as follows: “the process of investment choice can be broken down into two phases: first, the choice of a unique optimum combination of risky assets\(^1\); and second, a separate choice concerning the allocation of funds between such a combination and a single riskless asset”. This two-step procedure is today known as the mutual fund separation theorem. In this seminal research paper, Sharpe developed the CAPM theory and highlighted the relationship between the risk premium of the asset (the difference between the expected return and the risk-free rate) and its beta (the systematic risk with respect to the tangency portfolio). By assuming that the market is at equilibrium, he showed that the prices of assets are such that the tangency portfolio is the market portfolio, which is composed of all risky assets in proportion to their market capitalization.

The efficient frontier

The optimization problem  Seventy years ago, Markowitz introduced the concept of the efficient frontier. We consider a universe of \( n \) assets. Let \( w = (w_1, \ldots, w_n) \) be the vector of weights in the portfolio. We assume that the portfolio is fully invested meaning that \( \sum_{i=1}^{n} w_i = 1 \Rightarrow w^\top w = 1 \). We denote \( R = (R_1, \ldots, R_n) \) the vector of asset returns where \( R_i \) is the return of asset \( i \). The return of the portfolio is then equal to \( R(w) = \sum_{i=1}^{n} w_i R_i = w^\top R \). Let \( \mu = \mathbb{E}[R] \) and \( \Sigma = \mathbb{E}[(R - \mu)(R - \mu)^\top] \) be the vector of expected returns and the covariance matrix of asset returns. The expected return \( \mu(w) := \mathbb{E}[R(w)] \) of the portfolio is equal to:

\[
\mu(w) = \mathbb{E}[w^\top R] = w^\top \mathbb{E}[R] = w^\top \mu
\]

whereas its variance \( \sigma^2(w) := \text{var}(R(w)) \) is given by:

\[
\sigma^2(w) = \mathbb{E}[(R(w) - \mu(w))(R(w) - \mu(w))^\top]
= \mathbb{E}[w^\top (R - \mu)(R - \mu)^\top w]
= w^\top \Sigma w
\]

We can then formulate the investor’s financial problem as follows:

1. Maximizing the expected return of the portfolio under a volatility constraint (\( \sigma \)-problem):

\[
\max \mu(w) \quad \text{s.t.} \quad \sigma(w) \leq \sigma^*
\]  

\(^1\)It is precisely the tangency portfolio.
Chapter 3. Impact of ESG Investing on Asset Prices and Portfolio Returns

131

2. Or minimizing the volatility of the portfolio under a return constraint (µ-problem):
min σ (w)

s.t. µ (w) ≥ µ?

(3.2)


By considering all the portfolios belonging to the simplex set defined by w ∈ [0, 1]n : 1> w = 1 ,
we can compute the expected return and volatility bounds of the portfolios: µ− ≤ µ (w) ≤ µ+ and
σ − ≤ σ (w) ≤ σ + . There is also a solution to the first problem if σ ? ≥ σ − . The second problem
has a solution if µ? ≤ µ+ . If these two conditions are verified, the inequality constraints becomes
σ (w) = min (σ ? , σ + ) and µ (w) = max (µ− , µ? ).
The key idea of Markowitz (1956) was to transform the original non-linear optimization problem
(3.1) into a quadratic optimization problem which is easier to solve numerically. For that, he
introduced the mean-variance (or quadratic) utility function:
U (w) := E [R (w)] −

γ̄
γ̄
var (R (w)) = w> µ − w> Σw
2
2

where γ̄ is the absolute risk-aversion parameter. We obtain the following problem:
n
o
γ̄
w? (γ̄) = arg max U (w) = w> µ − w> Σw
2
s.t. 1> w = 1

(3.3)

If γ̄ = 0, the optimized portfolio is the one that maximizes the expected return and we have
µ (w? (0)) = µ+ . If γ̄ = ∞, the risk-aversion parameter is maximum, we obtain the global minimum
variance (GMV) portfolio:
w? (∞)

1
arg min w> Σw
2
>
s.t. 1 w = 1
=

and we have σ (w? (∞)) = σ − . In practice, we formulate the optimization problem (3.3) as follows:
w? (γ)

1
arg min w> Σw − γw> µ
2
>
s.t. 1 w = 1
=

(3.4)

where γ = γ̄ −1 is the inverse of the risk-aversion parameter and is called the risk-tolerance coefficient.
The reason is that this new formulation is a standard quadratic programming (QP) problem2 . From
a numerical point of view, it is therefore better to use Problem (3.4). In this case, the minimum
variance portfolio corresponds to γ = 0. The set of solutions {w? (γ) , γ ≥ 0} corresponds to meanvariance optimized (MVO) portfolios.
Example 9 We consider an investment universe of five assets. Their expected returns are equal to
5%, 7%, 6%, 10% and 8% while their volatilities are equal to 18%, 20%, 22%, 25% and 30%. The
correlation matrix of asset returns is given by the following matrix:


100%
 70% 100%





C =  20% 30% 100%

 −30% 20% 10% 100%

0%
0%
0%
0% 100%
Handbook of Sustainable Finance


In Figure 3.1, we report the efficient frontier \( \{ \sigma (w^* (\gamma)), \mu (w^* (\gamma)) \} \) by considering several values\(^3\) of \( \gamma \in [-0.5, 1] \). We note that optimized portfolios substantially improve the risk/return profile with respect to the five assets, which are represented by a cross symbol. Some special solutions are given in Table 3.1. The portfolio weights, its return and its volatility are expressed in \%. For instance, the GMV portfolio is obtained with \( \gamma = 0 \). The solution is \((66.35\%, -28.52\%, 15.31\%, 34.85\%, 12.02\%)\) and it is not possible to find a portfolio whose volatility is lower than \(10.40\%\).

### Table 3.1: Solution of the Markowitz optimization problem (in \%)

<table>
<thead>
<tr>
<th>( \gamma )</th>
<th>0.00</th>
<th>0.10</th>
<th>0.20</th>
<th>0.50</th>
<th>1.00</th>
<th>5.00</th>
</tr>
</thead>
<tbody>
<tr>
<td>( w^*_1 (\gamma) )</td>
<td>66.35</td>
<td>58.25</td>
<td>50.14</td>
<td>25.84</td>
<td>-14.67</td>
<td>-338.72</td>
</tr>
<tr>
<td>( w^*_2 (\gamma) )</td>
<td>-28.52</td>
<td>-22.67</td>
<td>-16.82</td>
<td>0.74</td>
<td>30.00</td>
<td>264.12</td>
</tr>
<tr>
<td>( w^*_3 (\gamma) )</td>
<td>15.31</td>
<td>13.30</td>
<td>11.30</td>
<td>5.28</td>
<td>-4.74</td>
<td>-84.93</td>
</tr>
<tr>
<td>( w^*_4 (\gamma) )</td>
<td>34.85</td>
<td>37.65</td>
<td>40.44</td>
<td>48.82</td>
<td>62.78</td>
<td>174.50</td>
</tr>
<tr>
<td>( w^*_5 (\gamma) )</td>
<td>12.02</td>
<td>13.48</td>
<td>14.94</td>
<td>19.32</td>
<td>26.62</td>
<td>85.03</td>
</tr>
<tr>
<td>( \mu (w^* (\gamma)) )</td>
<td>6.69</td>
<td>6.97</td>
<td>7.25</td>
<td>8.09</td>
<td>9.49</td>
<td>20.71</td>
</tr>
<tr>
<td>( \sigma (w^* (\gamma)) )</td>
<td>10.40</td>
<td>10.53</td>
<td>10.93</td>
<td>13.35</td>
<td>19.71</td>
<td>84.38</td>
</tr>
</tbody>
</table>

Solving the \( \mu \)-problem or the \( \sigma \)-problem is equivalent to finding the optimal value of \( \gamma \) such that \( \mu (w^* (\gamma)) = \mu^* \) or \( \sigma (w^* (\gamma)) = \sigma^* \). We know that the functions \( \mu (w^* (\gamma)) \) and \( \sigma (w^* (\gamma)) \)

\(^2\)See Appendix A.1.2 on page 576.

\(^3\)When \( \gamma < 0 \), \( w^* (\gamma) \) is not a MVO portfolio since it has a lower expected return than the GMV portfolio with a higher volatility. In fact, Problem (3.4) defines the convex hull \( \{ \mu (w), \sigma (w) \} \) of all possible portfolios \( \{ w : 1 \top w = 1 \} \).
are increasing with respect to $\gamma$ and are bounded. The optimal value of $\gamma$ can then be easily
computed using the bisection algorithm described on page A.1.2. This is the approach used in
practice, because it benefits from the numerical efficiency of quadratic programming solvers. For
instance, if we target a portfolio with $\sigma^* = 15\%$, we know that $\gamma \in [0.5, 1]$. The optimal solution $w^*$
is $(14.06\%, 9.25\%, 2.37\%, 52.88\%, 21.44\%)$. The bisection algorithm returns $\gamma = 0.6455$. In this case,
we obtain $\mu(w^*(\gamma)) = 8.50\%$. Let us now consider a $\mu$-problem with $\mu^* = 9\%$. We find $\gamma = 0.8252$,
$w^* = (-0.50\%, 19.77\%, -1.23\%, 57.90\%, 24.07\%)$ and $\sigma(w^*(\gamma)) = 17.30\%$.

Adding some constraints The Lagrange function of the optimization problem (3.4) is equal to:

$$L(w; \lambda) = \frac{1}{2} w^\top \Sigma w - \gamma w^\top \mu + \lambda_0 \left(1^\top w - 1\right)$$

where $\lambda_0$ is the Lagrange coefficients associated with the constraint $1^\top w = 1$. The solution $w^*$
verifies the following first-order conditions:

$$
\begin{align*}
\partial_w L(w; \lambda_0) &= \Sigma w - \gamma \mu + \lambda_0 1 = 0 \\
\partial_{\lambda_0} L(w; \lambda_0) &= 1^\top w - 1 = 0
\end{align*}
$$

We obtain $w = \Sigma^{-1}(\gamma \mu - \lambda_0 1)$. Because $1^\top w - 1 = 0$, we have $\gamma 1^\top \Sigma^{-1} \mu - \lambda_0 1^\top \Sigma^{-1} 1 = 1$. It
follows that:

$$\lambda_0 = \frac{\gamma 1^\top \Sigma^{-1} \mu - 1}{1^\top \Sigma^{-1} 1}$$

The solution is then:

$$w^*(\gamma) = \frac{\Sigma^{-1} 1}{1^\top \Sigma^{-1} 1} + \frac{(1^\top \Sigma^{-1} 1) \Sigma^{-1} \mu - (1^\top \Sigma^{-1} \mu) \Sigma^{-1} 1}{1^\top \Sigma^{-1} 1}$$

$$w_{gmv} = \frac{(\Sigma^{-1} 1)}{(1^\top \Sigma^{-1} 1)}$$

$$w_{sp} = \frac{(\Sigma^{-1} 1) \Sigma^{-1} \mu - (1^\top \Sigma^{-1} \mu) \Sigma^{-1} 1}{1^\top \Sigma^{-1} 1}$$

where $w_{gmv} = (\Sigma^{-1} 1) / (1^\top \Sigma^{-1} 1)$ is the global minimum variance portfolio and $w_{sp}$ is a
long/short cash-neutral portfolio such that $1^\top w_{sp} = 0$.

We deduce that a QP solver is not required to find the solution of the optimization problem (3.4).
For instance, the analytical calculus gives $w_{gmv} = (66.35\%, -28.52\%, 15.31\%, 34.85\%, 12.02\%)$ and
$w_{sp} = (-81.01\%, 58.53\%, -20.05\%, 27.93\%, 14.60\%)$. Using numerical results in Table 3.1, we verify
that the equation $w^*(\gamma) = w_{gmv} + \gamma w_{sp}$ is satisfied. Nevertheless, these solutions are not realistic,
because they correspond to leveraged long/short portfolios, but most of investors can not have
short positions. Moreover, short selling can only be implemented a few number of assets, which are
very liquid and highly tradable. Otherwise, the cost of short selling is huge. This is why portfolio
optimization in practice considers other constraints:

$$w^*(\gamma) = \arg \min w \frac{1}{2} w^\top \Sigma w - \gamma w^\top \mu$$

s.t. $$
\begin{align*}
1^\top w &= 1 \\
w &\in \Omega
\end{align*}
$$

where $w \in \Omega$ corresponds to the set of restrictions. The most frequent constraints are certainly the
no short-selling restriction and asset bounds. In the first case, $w_i \geq 0$ and $\Omega = [0, 1]^n$. The second

\footnote{From a numerical point of view, it is generally better to solve several QP problems than one non-linear optimization
problem.}

\footnote{We have $1^\top w^*(\gamma) = 1 \Leftrightarrow 1^\top w_{gmv} + \gamma 1^\top w_{sp} = 1 \Leftrightarrow 1^\top w_{sp} = 0$ because $1^\top w_{gmv} = 1$.}
constraint imposes \( w_i \leq w^+ \), in order to be sure that the portfolio is not concentrated in a few number of assets.

Let us introduce some constraints in Example 9. In Figure 3.2, we have reported two constrained efficient frontiers, the first one by imposing no short-selling and the second one by imposing that the weights are between 0% and 33%. We verify that investment constraints may substantially reduce opportunity arbitrages.

**Figure 3.2: Impact of constraints on the efficient frontier (Example 9)**

\[
\text{The tangency portfolio}
\]

**Two-fund separation theorem**  We recall that in the view of Markowitz, there is a set of optimized portfolios. However, Tobin (1958) showed that one optimized portfolio dominates all the others if there is a risk-free asset. Let us consider a combination of the risk-free asset and a portfolio \( w \). We denote \( r \) the return of the risk-free asset. We have:

\[
R(\tilde{w}) = (1 - \alpha) r + \alpha R(w)
\]

where \( \tilde{w} = (\alpha w, 1 - \alpha) \) is a vector of dimension \((n + 1)\) and \( \alpha \geq 0 \) is the proportion of the wealth invested in the risky portfolio. It follows that:

\[
\mu(\tilde{w}) = (1 - \alpha) r + \alpha \mu(w) = r + \alpha (\mu(w) - r)
\]

and:

\[
\sigma^2(\tilde{w}) = \alpha^2 \sigma^2(w)
\]

\(^6\text{We have } n + 1 \text{ assets in the universe where the first } n \text{ assets correspond to the previous risky assets and the last asset is the risk-free asset.}\)

_Handbook of Sustainable Finance_
We deduce that:

\[ \mu(\tilde{w}) = r + \frac{\mu(w) - r}{\sigma(w)} \sigma(\tilde{w}) \]  

(3.6)

It is the equation of a linear function between the volatility and the expected return of the combined portfolio \( \tilde{w} \). In Figure 3.3, we reported the previous (unconstrained) efficient frontier. The dashed line corresponds to the combination between the risk-free asset (\( r \) is equal to 3%) and the optimized portfolio \( w^* \). Nevertheless this combination is suboptimal, because it is dominated by other combinations. We note that a straight line dominates all the other straight lines and the efficient frontier. This line is tangent to the efficient frontier and is called the capital market line. It implies that one optimized risky portfolio dominates all the other risky portfolios, namely the tangency portfolio. We denote it by \( w^* \).

Figure 3.3: Capital market line (Example 9)

Let \( \text{SR}(w \mid r) \) be the Sharpe ratio of portfolio \( w \):

\[ \text{SR}(w \mid r) = \frac{\mu(w) - r}{\sigma(w)} \]

We note that we can write Equation (3.6) as follows:

\[ \frac{\mu(\tilde{w}) - r}{\sigma(\tilde{w})} = \frac{\mu(w) - r}{\sigma(w)} \iff \text{SR}(\tilde{w} \mid r) = \text{SR}(w \mid r) \]

We deduce that the tangency portfolio is the one that maximizes the angle \( \theta(w) \) or equivalently \( \tan \theta(w) \) which is equal to the Sharpe ratio. The tangency portfolio is also the risky portfolio corresponding to the maximum Sharpe ratio. We also note that any portfolio which belongs to the capital market line has the same Sharpe ratio. If we consider our example with \( r = 3\% \), the composition of the tangency portfolio \( w^* \) is (42.57%, -11.35%, 9.43%, 43.05%, 16.30%) and we have \( \mu(w^*) = 7.51\% \), \( \sigma(w^*) = 11.50\% \), \( \text{SR}(w^* \mid r) = 0.39 \) and \( \theta(w^*) = 21.40 \) degrees.
Augmented optimization problem  When the risk-free asset belongs to the investment universe, the optimization problem becomes:

$$
\tilde{w}^* (\gamma) = \arg \min \frac{1}{2} \tilde{w}^T \tilde{\Sigma} \tilde{w} - \gamma \tilde{w}^T \tilde{\mu}
$$

s.t.  $$
\begin{align*}
1^T \tilde{w} &= 1 \\
\tilde{w} &\in \Omega
\end{align*}
$$

where $\tilde{w} = (w, w_r)$ is the augmented allocation vector of dimension $n + 1$. It follows that:

$$
\tilde{\Sigma} = \begin{pmatrix} \Sigma & 0 \\ 0 & 0 \end{pmatrix} \quad \text{and} \quad \tilde{\mu} = \begin{pmatrix} \mu \\ r \end{pmatrix}
$$

In the case where $\Omega = \mathbb{R}^{n+1}$, Roncalli (2013, pages 13-14) showed that the optimal solution is equal to:

$$
\tilde{w}^* (\gamma) = \alpha \cdot \begin{pmatrix} w^* \\ 0 \end{pmatrix} + (1 - \alpha) \cdot \begin{pmatrix} 0 \\ 1 \end{pmatrix}
$$

where $w^*$ is the tangency portfolio:

$$
w^* = \frac{\Sigma^{-1} (\mu - r 1)}{1^T \Sigma^{-1} (\mu - r 1)}
$$

and the proportion of risky assets is equal to $\alpha = \gamma 1^T \Sigma^{-1} (\mu - r 1)$. It follows that the risk-tolerance coefficient associated to the tangency portfolio is given by:

$$
\gamma (w^*) = \frac{1}{1^T \Sigma^{-1} (\mu - r 1)}
$$

When $\alpha \neq 1$, the weights $\tilde{w}^* (\gamma)$ of the optimal portfolio are proportional to the weights $w^*$ of the tangency portfolio whereas the wealth invested in the risk-free asset is the complement $(1 - \alpha)$ to obtain a total exposure equal to 100%. We retrieve then the two-fund separation theorem.

Market equilibrium and CAPM

Risk premium and beta  Based on the results of Markowitz and Tobin, Sharpe (1964) developed the capital asset pricing model (CAPM). Let $w^*$ be the tangency portfolio. On the efficient frontier, we have seen that any portfolio $w$ satisfies the capital market line:

$$
\mu (w) = r + \frac{\sigma (w)}{\sigma (w^*)} (\mu (w^*) - r)
$$

We consider a portfolio $x$ with a proportion $\omega$ invested in the asset $i$ and a proportion $(1 - \omega)$ invested in the tangency portfolio $w^*$. We have $\mu (x) = \omega \mu_i + (1 - \omega) \mu (w^*)$ and $\sigma^2 (x) = \omega^2 \sigma_i^2 + (1 - \omega)^2 \sigma^2 (w^*) + 2 \omega (1 - \omega) \rho (e_i, w^*) \sigma_i \sigma (w^*)$. It follows that:

$$
\frac{\partial \mu (x)}{\partial \sigma (x)} = \frac{\mu_i - \mu (w^*)}{(\omega \sigma_i^2 + (\omega - 1) \sigma^2 (w^*) + (1 - 2 \omega) \rho (e_i, w^*) \sigma_i \sigma (w^*)) \sigma^{-1} (x)}
$$

$^7e_i$ is the unit vector with 1 in the $i^{th}$ position and 0 elsewhere. It corresponds then to the portfolio fully invested in asset $i$. 

Handbook of Sustainable Finance
When $\omega = 0$, the portfolio $x$ is the tangency portfolio $w^*$ and the previous derivative is equal to the Sharpe ratio $\text{SR} (w^* \mid r)$:

$$
\lim_{\omega \to 0} \frac{\partial \mu (x)}{\partial \sigma (x)} = \tan \theta (w^*) = \frac{\mu (w^*) - r}{\sigma (w^*)}
$$

We deduce that:

$$
\frac{(\mu_i - \mu (w^*)) \sigma (w^*)}{\rho (e_i, w^*) \sigma (w^*) - \sigma^2 (w^*)} = \frac{\mu (w^*) - r}{\sigma (w^*)}
$$

which is equivalent to:

$$
\pi_i := \mu_i - r = \beta_i (\mu (w^*) - r) \quad (3.8)
$$

where $\pi_i$ is the risk premium of the asset $i$ and:

$$
\beta_i = \frac{\rho (e_i, w^*) \sigma_i}{\sigma (w^*)} = \frac{\text{cov} (R_i, R (w^*))}{\text{var} (R (w^*))} \quad (3.9)
$$

The coefficient $\beta_i$ is the ratio of the covariance between the return of asset $i$ and the return of the tangency portfolio upon the variance of the tangency portfolio return. Equation (3.8) tells us that the risk premium of the asset $i$ is equal to its beta times the excess return of the tangency portfolio. It is easy to show that this relationship remains valid for any portfolio $w$ and not only for the assets that compose the tangency portfolio.

**Box 3.1: Computation of the beta coefficient**

Let $R_{i,t}$ and $R_t (w)$ be the returns of asset $i$ and portfolio $w$ at time $t$. We consider the linear regression:

$$
R_{i,t} = \alpha_i + \beta_i R_t (w) + \varepsilon_{i,t}
$$

where $\varepsilon_{i,t}$ is a white noise process. The OLS coefficient $\hat{\beta}_i$ is an estimate of the beta $\beta_i$ of the asset $i$. We can generalize this approach to estimate the beta of one portfolio $x$ with respect to another portfolio $w$. We have:

$$
R_t (x) = \alpha + \beta R_t (w) + \varepsilon_t
$$

Another way to compute the beta is to use the following relationship:

$$
\beta (x \mid w) = \frac{\sigma (x, w)}{\sigma^2 (w)} = \frac{x^\top \Sigma w}{w^\top \Sigma w}
$$

We deduce that the expression of the beta of asset $i$ is also:

$$
\beta_i = \beta (e_i \mid w) = \frac{e_i^\top \Sigma w}{w^\top \Sigma w} = \frac{(\Sigma w)_i}{w^\top \Sigma w}
$$

It follows that the beta of a portfolio is the weighted average of the beta of the assets that compose the portfolio:

$$
\beta (x \mid w) = \frac{x^\top \Sigma w}{w^\top \Sigma w} = x^\top \frac{\Sigma w}{w^\top \Sigma w} = \sum_{i=1}^{n} x_i \beta_i
$$

The relationship (3.8) is very important and highlights the role of the beta coefficient. However, this result is not the only main finding of Sharpe (1964). In his article, Sharpe showed also that
if the market is at the equilibrium, the prices of assets are such that the tangency portfolio \( w^* \) is the market portfolio \( w_m \) (or the market-cap portfolio). With this result, the characterization of the tangency portfolio does not depend upon the assumptions about expected returns, volatilities and correlations.

In the case of Example 9, we have seen that the composition of the tangency portfolio is \( w^* = (42.57\%, -11.35\%, 9.43\%, 43.05\%, 16.30\%) \). Since its expected return is \( \mu(w^*) = 7.51\% \) and \( r = 3\% \), we deduce that the market risk premium is equal to 4.51\%. In Table 3.2, we report the beta of each asset and two portfolios: the equally weighted (EW) portfolio \( w_{ew} \) and the GMV portfolio \( w_{gmv} \). We compute the associated expected return \( \mu(w) = w^\top \mu \) and the risk premium explained by the tangency portfolio \( \pi(w | w^*) = \beta(w | w^*) (\mu(w^*) - r) \). We verify the relationship \( \pi(w | w^*) = \mu(w) - r \). For instance, the beta of the first asset is equal to 0.444 and we have \( 0.444 \times 4.51\% = 2\% \), which is also equal to the difference between 5\% and 3\%. For the EW portfolio, the risk premium is equal to \( 0.932 \times 4.51\% = 4.20\% \). We also verify that it is equal to the difference between the expected return 7.20\% and the risk-free rate 3\%.

| Portfolio | \( \mu(w) \) | \( \mu(w) - r \) | \( \beta(w | w^*) \) | \( \pi(w | w^*) \) |
|-----------|-------------|----------------|----------------|----------------|
| \( e_1 \) | 5.00\%      | 2.00\%         | 0.444          | 2.00\%         |
| \( e_2 \) | 7.00\%      | 4.00\%         | 0.887          | 4.00\%         |
| \( e_3 \) | 6.00\%      | 3.00\%         | 0.665          | 3.00\%         |
| \( e_4 \) | 10.00\%     | 7.00\%         | 1.553          | 7.00\%         |
| \( e_5 \) | 8.00\%      | 5.00\%         | 1.109          | 5.00\%         |
| \( w_{ew} \) | 7.20\%      | 4.20\%         | 0.932          | 4.20\%         |
| \( w_{gmv} \) | 6.69\%      | 3.69\%         | 0.817          | 3.69\%         |

**Risk premium and alpha return**  
Jensen (1968) analyzed the performance of active management by using the following regression model:

\[
R_{j,t} - r = \alpha_j + \beta_j (R_t(w_m) - r) + \varepsilon_{j,t}
\]

where \( R_{j,t} \) is the return of the mutual fund \( j \) at time \( t \), \( R_t(w_m) \) is the return of the market portfolio and \( \varepsilon_{j,t} \) is an idiosyncratic risk. If the mutual fund outperforms the market portfolio, the assumption \( \alpha_j > 0 \) is not rejected. However, Jensen rejected this assumption for most mutual funds and concluded that active management did not create alpha. More generally, the alpha is defined by the difference between the risk premium \( \pi(w) \) of portfolio \( w \) and the beta\(^8\) \( \beta(w) \) of the portfolio times the market risk premium \( \pi_m \):

\[
\alpha = (\mu(w) - r) - \beta(w | w_m)(\mu(w_m) - r) = \pi(w) - \beta(w)\pi_m
\]

If we now impose a no short-selling constraint by using a lower bound \( x_i \geq 0 \), the tangency portfolio becomes \( w^* = (33.62\%, 0\%, 8.79\%, 40.65\%, 16.95\%) \) in our previous example. We verify that the portfolio has not a short exposure on the second asset. Since we have \( \mu(w^*) = 7.63\% \) and \( r = 3\% \), we deduce that the market risk premium is equal to 4.63\%. It is higher than in the unconstrained case. We report the beta and the risk premium in Table 3.3. We notice that the equality \( \mu(w) - r = \)

\(^8\)The notation \( \beta(w) \) means that the beta is computed with respect to the market portfolio.
Box 3.2: Computing the implied risk premia of investors

Let us consider the optimization problem:

\[
\begin{align*}
    w^* &= \arg \min \frac{1}{2} w^\top \Sigma w - \gamma w^\top (\mu - r1) \\
    \text{s.t.} & \quad \{ 1^\top w = 1 \} \\
    & \quad w \in \Omega
\end{align*}
\]

If we omit the constraints, the solution is \( w^* = \gamma \Sigma^{-1} (\mu - r1) \). In the Markowitz model, the unknown variable is the vector \( w \) of weights. We now suppose that the investor has a current asset allocation \( w_0 \). By construction, \( w_0 \) is the optimal portfolio for this investor, otherwise he will change its investment policy. We deduce that:

\[
w_0 = \gamma \Sigma^{-1} (\mu - r1) \Leftrightarrow \tilde{\pi} = \mu - r1 = \frac{1}{\gamma} \Sigma w_0
\]

(3.10)

We may interpret \( \tilde{\pi} \) as the vector of risk premia which is coherent with the portfolio \( w_0 \) (Black and Litterman, 1991, 1992). \( \tilde{\pi} \) is then the risk premium priced by the portfolio manager. The computation of \( \tilde{\pi} \) requires to specify the risk tolerance of the investor. Let us assume that the investor targets a Sharpe ratio \( \text{SR}(w_0 | r) \) for his portfolio. We deduce that:

\[
\text{SR}(w_0 | r) = \frac{\mu(w_0) - r}{\sigma(w_0)} = \frac{w_0^\top (\mu - r1)}{\sqrt{w_0^\top \Sigma w_0}} = \frac{1}{\gamma} \sqrt{w_0^\top \Sigma w_0}
\]

Finally, we obtain:

\[
\tilde{\pi} = \text{SR}(w_0 | r) \cdot \frac{\Sigma w_0}{\sqrt{w_0^\top \Sigma w_0}}
\]

Let us consider Example 9. We suppose that the current allocation \( w_0 \) is equal to \((35\%, 25\%, 15\%, 15\%, 10\%)\). The volatility of the portfolio is then equal to \( \sigma(x_0) = 12.52\% \). The objective of the portfolio manager is to target a Sharpe ratio equal to 0.25. The implied risk tolerance is \( \gamma = 0.50 \) and the implied risk premia are \( \tilde{\pi} = (3.36\%, 4.45\%, 2.83\%, 1.59\%, 1.80\%) \).

\( ^a \)We notice that the excess expected return is equal to \( w^\top (\mu - r1) = w^\top \mu - r \). Adding the risk-free rate has then no impact on the mean-variance utility function.

\( ^b \)From this equation, we also deduce the following relationship: \( \tilde{\pi}(w_0) = \gamma^{-1} \sigma^2(w_0) \).

\( \beta(w)(\mu_m - r) \) is not always satisfied. This is particularly true for the second asset, which has a negative alpha of 49 bps. We know that the true risk premium of this asset is 4\%. Nevertheless, investors are constrained and they can not short this asset. From a theoretical point of view, the optimal demand for this asset must be negative. Because of the lower bound \( x_i \geq 0 \), the market demand is higher than the expected demand deduced from the CAPM. Therefore, there is a price pressure on this asset due to a lack of arbitrage. The risk premium perceived by the market is then higher, creating a negative alpha because the price is overvalued. As the equally-weighted portfolio is long on this asset, it has also a negative alpha. This is not the case of the GMV portfolio, which is short on this asset (its weight is equal to \(-28.52\% \) — see Table 3.1 on page 132).
Table 3.3: Computation of the alpha return (Example 9)

<table>
<thead>
<tr>
<th>Portfolio</th>
<th>( \mu (w) )</th>
<th>( \mu (w) - r )</th>
<th>( \beta (w \mid w^*) )</th>
<th>( \pi (w \mid w^*) )</th>
<th>( \alpha (w \mid w^*) )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( e_1 )</td>
<td>5.00%</td>
<td>2.00%</td>
<td>0.432</td>
<td>2.00%</td>
<td>0.00%</td>
</tr>
<tr>
<td>( e_2 )</td>
<td>7.00%</td>
<td>4.00%</td>
<td>0.970</td>
<td>4.49%</td>
<td>-0.49%</td>
</tr>
<tr>
<td>( e_3 )</td>
<td>6.00%</td>
<td>3.00%</td>
<td>0.648</td>
<td>3.00%</td>
<td>0.00%</td>
</tr>
<tr>
<td>( e_4 )</td>
<td>10.00%</td>
<td>7.00%</td>
<td>1.512</td>
<td>7.00%</td>
<td>0.00%</td>
</tr>
<tr>
<td>( e_5 )</td>
<td>8.00%</td>
<td>5.00%</td>
<td>1.080</td>
<td>5.00%</td>
<td>0.00%</td>
</tr>
<tr>
<td>( \omega_{ew} )</td>
<td>7.20%</td>
<td>4.20%</td>
<td>0.929</td>
<td>4.30%</td>
<td>-0.10%</td>
</tr>
<tr>
<td>( \omega_{gmv} )</td>
<td>6.69%</td>
<td>3.69%</td>
<td>0.766</td>
<td>3.55%</td>
<td>0.14%</td>
</tr>
</tbody>
</table>

The previous analysis can be applied to a more general framework. There are two main explanations of alpha generation. The first one concerns the assumptions of the CAPM. In particular, this model assumes that investors face no constraints in terms of leverage, short selling, transaction costs, etc. In practice, investors are highly constrained, especially large institutional investors. Since they can not leverage their portfolios, they do not use the tangency portfolio. They will prefer a portfolio with a lower Sharpe ratio, but with a higher expected return. This explains that the demand for high beta assets is greater than the demand predicted by the CAPM. Therefore, we observe a positive alpha return for low-beta assets and a negative alpha return for high-beta assets (Black, 1972; Frazzini and Pedersen, 2014). The second explanation is the existence of other risk factors, which are not priced by the CAPM (Ross, 1976). The development of factor investing and alternative risk premia in the aftermath of the 2008 global financial crisis is related to this issue. If investors use systematic strategies with the same approach and these strategies are very popular, they may impact asset prices (Roncalli, 2017). In both cases, alpha generation takes its root in the imbalance between supply and demand and the dynamics of investment flows.

**Utility function revisited**

The Markowitz approach for portfolio optimization assumes that the investor has a mean-variance utility function without any reference to a given investment policy. We now extend the optimization problem when a strategic asset allocation imposes a benchmark, which is represented by a portfolio \( b \). The tracking error between the active portfolio \( w \) and its benchmark \( b \) is the difference between the return of the portfolio and the return of the benchmark:

\[
\epsilon = R(w) - R(b) = \sum_{i=1}^{n} w_i R_i - \sum_{i=1}^{n} b_i R_i = w^\top R - b^\top R = (w - b)^\top R
\]

The tracking error \( \epsilon \) is a stochastic random variable. The expected excess return is equal to:

\[
\mu (w \mid b) := \mathbb{E}[\epsilon] = (w - b)^\top \mu
\]

whereas the volatility of the tracking error is defined as:

\[
\sigma (w \mid b) := \sigma (\epsilon) = \sqrt{(w - b)^\top \Sigma (w - b)}
\]

The objective of the investor is then to maximize the expected tracking error with a constraint on the tracking error volatility:

\[
w^* = \arg \max \mu (w \mid b) \quad \text{s.t.} \quad \begin{cases} 1^\top x = 1 \\ \sigma (w \mid b) \leq \sigma^* \end{cases}
\]
Like the Markowitz problem, we transform this $\sigma$-problem into a $\gamma$-problem:

$$w^* (\gamma) = \arg \min f (w \mid b)$$

where:

$$f (w \mid b) = \frac{1}{2} \sigma^2 (w \mid b) - \gamma \mu (w \mid b)$$

$$= \frac{1}{2} (w - b)^\top \Sigma (w - b) - \gamma (w - b)^\top \mu$$

$$= \frac{1}{2} w^\top \Sigma w - w^\top (\gamma \mu + \Sigma b) + \frac{1}{2} b^\top \Sigma b + \gamma b^\top \mu$$

Again, we recognize a quadratic programming problem. The efficient frontier is then the parametric curve $(\sigma (w^* (\gamma) \mid b), \mu (w^* (\gamma) \mid b))$ with $\gamma \geq 0$.

**Remark 28** Using Equation (3.10), we notice that $w^\top (\gamma \mu + \Sigma b) = 2 \gamma w^\top \left( \pi + \tilde{\pi} \right) - \gamma$ where $\tilde{\pi}$ is the implied risk premia associated to the benchmark $b$. We obtain a Markowitz problem where the vector of expected returns is replaced by an average between the true and implied risk premia.

**Example 10** We consider an investment universe of four assets. Their expected returns are equal to 5%, 6.5%, 8% and 6.5% while their volatilities are equal to 15%, 20%, 25% and 30%. The correlation matrix of asset returns is given by the following matrix:

$$C = \begin{pmatrix}
100 & 10 & 100 \\
10 & 100 & 40 \\
100 & 40 & 80 \\
100 & 80 & 100
\end{pmatrix}$$

We consider Example 10 with the benchmark $b = (60\%, 40\%, 20\%, -20\%)$. In Figure 3.4, we have represented the corresponding efficient frontier. We verify that it is a straight line when there is no restriction (Roll, 1992). If we impose that $w_i \geq -10\%$, the efficient frontier is moved to the right. For the third case, we assume that the weights are between a lower bound and an upper bound: $w_i^- \leq w_i \leq w_i^+$ with $w_i^+ = 50\%$. For the first three assets, the lower bound $w_i^-$ is set to 0, whereas it is equal to $-20\%$ for the fourth asset.

**Information ratio** To compare the performance of different portfolios, a better measure than the Sharpe ratio is the information ratio which is defined as follows:

$$\text{IR} (w \mid b) = \frac{\mu (w \mid b)}{\sigma (w \mid b)} = \frac{(w - b)^\top \mu}{\sqrt{(w - b)^\top \Sigma (w - b)}}$$

If we consider a combination of the benchmark $b$ and the active portfolio $w$, the composition of the portfolio is:

$$x = (1 - \alpha) b + \alpha w$$

where $\alpha \geq 0$ is the proportion of wealth invested in the portfolio $w$. It follows that:

$$\mu (x \mid b) = (x - b)^\top \mu = \alpha \mu (w \mid b)$$
Chapter 3. Impact of ESG Investing on Asset Prices and Portfolio Returns

Figure 3.4: Efficient frontier with a benchmark (Example 10)

Figure 3.5: Tangency portfolio with respect to a benchmark (Example 10)
and:
\[ \sigma^2 (x | b) = (x - b)^\top \Sigma (x - b) = \alpha^2 \sigma^2 (w | b) \]

We deduce that:
\[ \mu (x | b) = IR (w | b) \cdot \sigma (x | b) \]

It is the equation of a linear function between the tracking error volatility and the expected tracking error of the portfolio \( x \). It implies that the efficient frontier is a straight line:

“If the manager is measured solely in terms of excess return performance, he or she should pick a point on the upper part of this efficient frontier. For instance, the manager may have a utility function that balances expected value added against tracking error volatility. Note that because the efficient set consists of a straight line, the maximal Sharpe ratio is not a usable criterion for portfolio allocation” (Jorion, 2003, page 172).

If we add some other constraints to the portfolio optimization problem (3.11), the efficient frontier is no longer a straight line. In this case, one optimized portfolio dominates all the other portfolios. It is the portfolio which belongs to the efficient frontier and the straight line which is tangent to the efficient frontier. It is also the portfolio which maximizes the information ratio.

Let us look at the previous efficient frontier when we impose lower and upper bounds (third case). When we combine it with the benchmark, we obtain the straight line produced in Figure 3.5 and the tangency portfolio is equal to \((46.56\%, 33.49\%, 39.95\%, -20.00\%)\).

### 3.1.2 ESG risk premium

We now analyze the impact of ESG investing in the CAPM. However, it is important to reiterate that the risk premium is the expected excess return earned by investors because they are exposed to a systematic risk. Therefore, we must differentiate between expected (or required) returns and historical (or realized) returns. Moreover, it is not very clear whether the risk premium is a specific requirement from investors or the long-term performance. This is the difference between the unconstrained risk premium \( \pi_i \) and the implied risk premium \( \tilde{\pi}_i \).

**The Pastor-Stambaugh-Taylor model**

In this section, we present the model developed by Pástor et al. (2021) (hereafter, PST model). It is a direct extension of the CAPM and has the advantage to highlights many intuitive stylized facts.

**Model settings** Pástor et al. (2021) consider an investment universe of \( n \) assets corresponding to the shares of \( n \) firms. They assume that the asset excess returns \( \tilde{R} = R - r = \left( \tilde{R}_1, \ldots, \tilde{R}_n \right) \) are normally distributed — \( \tilde{R} \sim \mathcal{N}(\pi, \Sigma) \), and the firms produce social impact. Each firm has an ESG characteristic \( G_i \), which is positive for esg-friendly (or green) firms and negative for esg-unfriendly (or brown) firms. This means that \( G_i > 0 \) induces positive social impact, while \( G_i < 0 \) induces negative externalities on the society. They consider an economy with a continuum of agents \( (j = 1, 2, \ldots, \infty) \). We note \( w_{i,j} \) the fraction of the wealth invested by agent \( j \) in stock \( i \), and \( w_j = (w_{1,j}, \ldots, w_{n,j}) \) the allocation vector of agent \( j \). The relationship between the initial and terminal wealth \( W_j \) and \( \tilde{W}_j \) is given by:

\[ \tilde{W}_j = (1 + r + w_j^\top \tilde{R}) W_j \]

Pástor et al. (2021) assume that the economic agent \( j \) has an exponential CARA utility function:

\[ U \left( \tilde{W}_j, w_j \right) = -\exp \left( -\gamma_j \tilde{W}_j - w_j^\top b_j W_j \right) \]
where \( \gamma_j \) is the absolute risk-aversion and \( b_j = \varphi_j \mathcal{G} \) is the vector of nonpecuniary benefits that depends on the green intensity \( \mathcal{G} \) and the ESG preference coefficient \( \varphi_j \geq 0 \) of the economic agent.

**Optimal portfolio** The expected utility is equal to:

\[
\mathbb{E} \left[ \mathcal{U} \left( \tilde{W}_j, w_j \right) \right] = \mathbb{E} \left[ -\exp \left( -\tilde{\gamma}_j \tilde{W}_j - w_j^\top b_j \right) \right]
\]

\[
= \mathbb{E} \left[ -\exp \left( -\tilde{\gamma}_j \left( 1 + r + w_j^\top \tilde{R} \right) W_j - w_j^\top b_j \right) \right]
\]

\[
= -e^{-\tilde{\gamma}_j(1+r)\mathbb{E} \left[ \exp \left( -\gamma_j w_j^\top W_j \left( \tilde{R} + \tilde{\gamma}_j^{-1} b_j \right) \right) \right]}
\]

\[
= -e^{-\bar{\Gamma}_j(1+r)\mathbb{E} \left[ \exp \left( -\bar{\Gamma}_j w_j^\top \left( \tilde{R} + \tilde{\gamma}_j^{-1} b_j \right) \right) \right]}
\]

where \( \bar{\Gamma}_j = \tilde{\gamma}_j W_j \) is the nominal risk aversion. We notice that \( \tilde{R} + \tilde{\gamma}_j^{-1} b_j \sim \mathcal{N} \left( \pi + \tilde{\gamma}_j^{-1} b_j, \Sigma \right) \) and:

\[-\bar{\Gamma}_j w_j^\top \left( \tilde{R} + \tilde{\gamma}_j^{-1} b_j \right) \sim \mathcal{N} \left( -\bar{\Gamma}_j w_j^\top \left( \pi + \tilde{\gamma}_j^{-1} b_j \right), \bar{\Gamma}_j^2 w_j^\top \Sigma w_j \right)\]

Using the mathematical expectation formula of the log-normal distribution\(^9\), we deduce that:

\[
\mathbb{E} \left[ \mathcal{U} \left( \tilde{W}_j, w_j \right) \right] = e^{-\bar{\Gamma}_j(1+r)} \exp \left( -\bar{\Gamma}_j w_j^\top \left( \pi + \tilde{\gamma}_j^{-1} b_j \right) + \frac{1}{2} \bar{\Gamma}_j^2 w_j^\top \Sigma w_j \right)
\]

The first-order condition is equal to:

\[-\bar{\Gamma}_j \left( \pi + \tilde{\gamma}_j^{-1} b_j \right) + \bar{\Gamma}_j^2 \Sigma w_j = 0\]

Finally, Pástor et al. (2021) conclude that the optimal portfolio is:

\[w^*_j = \Gamma_j \Sigma^{-1} \left( \pi + \gamma_j b_j \right)\]

where \( \Gamma_j = \tilde{\gamma}_j^{-1} \) and \( \gamma_j = \tilde{\gamma}_j^{-1} \) are the relative risk-tolerance coefficients. This is the unconstrained optimal portfolio where asset returns include the green sentiment \( \gamma_j b_j = \gamma_j \varphi_j \mathcal{G} \).

**Remark 29** We assume that \( W_j = 1 \). Since we have \( 1^\top w_j = 1, w_j^\top r = r \) and \( \bar{\Gamma}_j = \gamma_j \), we deduce that:

\[-\ln \mathbb{E} \left[ \mathcal{U} \left( \tilde{W}_j, w_j \right) \right] = \tilde{\gamma}_j (1 + r) + \tilde{\gamma}_j w_j^\top \left( \pi + \tilde{\gamma}_j^{-1} b_j \right) - \frac{1}{2} \tilde{\gamma}_j^2 w_j^\top \Sigma w_j\]

\[\propto w_j^\top \left( \pi + r 1 + \tilde{\gamma}_j^{-1} b_j \right) - \frac{1}{2} \tilde{\gamma}_j w_j^\top \Sigma w_j\]

\[w_j^\top \left( \mu + \tilde{\gamma}_j^{-1} b_j \right) - \frac{1}{2} \tilde{\gamma}_j w_j^\top \Sigma w_j\]

Maximizing the expected utility is then equivalent to solve the classical Markowitz QP problem:

\[w_j^* (\gamma_j) = \arg \min \frac{1}{2} w_j^\top \Sigma w_j - \gamma_j w_j^\top \mu'\]

\[s.t. \quad 1^\top w_j = 1\]

where \( \gamma_j = \tilde{\gamma}_j^{-1} \) is the relative risk tolerance and \( \mu' = \mu + \gamma_j b_j \) is the vector of modified expected returns that takes into account the ESG sentiment of the economic agent concerning the social impact of firms.

\(^9\)See Appendix A.2.1 on page 584.

---

*Handbook of Sustainable Finance*
Example 11 We consider a universe of n risky assets, where n is an even number. The risk-free rate \( r \) is set to 3%. We assume that the Sharpe ratio of these assets is the same and is equal to 20%. The volatility of asset \( i \) is equal to \( \sigma_i = 0.10 + 0.20 \cdot e^{-n^{-1} [0.5i]} \). The correlation between asset returns is constant: \( \rho = C_n (\rho) \). The social impact of the firms is given by the vector \( \mathcal{G} \). When \( \mathcal{G} \) is not specified, it is equal to the cyclic vector \((+1\%, -1\%, +1\%, \ldots, +1\%, -1\%)\). This implies that half of the firms (green firms) have a positive social impact while the others (brown firms) have a negative impact.

We consider the case \( n = 6 \) and \( \rho = 25\% \), and we assume that we can not be short on the assets. We calibrate the risk-tolerance parameter \( \gamma \) such that the long-only optimized portfolio of the non-ESG investor has a volatility of 20%. We find \( \gamma = 1.5456 \) and obtain the results reported in Table 3.4. We verify that the optimized portfolio depends on the ESG preference coefficient \( \varphi \). We consider a second set of ESG characteristics: \( \mathcal{G} = (10\%, 5\%, 2\%, 3\%, 25\%, 30\%) \). Since \( \mathcal{G}_i > 0 \), we can consider that this investment universe has been filtered in order to keep only the best-in-class issuers and implement an ESG selection strategy. Again, we measure the impact of \( \varphi \) on the optimized portfolios. In Figure 3.6, we report the efficient frontier when the investment universe is made up of 20 assets. We verify that the expected returns of the efficient frontier are reduced when considering ESG preferences, and this reduction depends on the ESG preference coefficient \( \varphi \). We also notice that all these efficient frontiers start at the same point since the global minimum variance portfolio is not affected by the ESG taste of the investor.

Table 3.4: Mean-variance optimized portfolios with ESG preferences (Example 11, \( n = 6 \), \( \rho = 25\% \))

<table>
<thead>
<tr>
<th>( \varphi )</th>
<th>( \mathcal{G} = (1%, -1%, 1%, -1%, 1%, -1%) )</th>
<th>( \mathcal{G} = (10%, 5%, 2%, 3%, 25%, 30%) )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( w^*_1 )</td>
<td>44.97% 48.87% 58.65% 67.48%</td>
<td>44.97% 46.83% 28.69% 0.00%</td>
</tr>
<tr>
<td>( w^*_2 )</td>
<td>44.97% 41.06% 19.60% 0.00%</td>
<td>44.97% 37.06% 9.17% 0.00%</td>
</tr>
<tr>
<td>( w^*_3 )</td>
<td>5.03% 9.82% 21.75% 32.52%</td>
<td>5.03% 0.00% 0.00% 0.00%</td>
</tr>
<tr>
<td>( w^*_4 )</td>
<td>5.03% 0.25% 0.00% 0.00%</td>
<td>5.03% 0.00% 0.00% 0.00%</td>
</tr>
<tr>
<td>( w^*_5 )</td>
<td>0.00% 0.00% 0.00% 0.00%</td>
<td>0.00% 0.83% 16.62% 21.09%</td>
</tr>
<tr>
<td>( w^*_6 )</td>
<td>0.00% 0.00% 0.00% 0.00%</td>
<td>0.00% 15.28% 45.53% 78.91%</td>
</tr>
<tr>
<td>( \mu (w^*) )</td>
<td>8.33% 8.33% 8.27% 8.22%</td>
<td>8.33% 8.23% 7.79% 7.43%</td>
</tr>
<tr>
<td>( \sigma (w^*) )</td>
<td>20.00% 20.09% 20.07% 21.56%</td>
<td>20.00% 19.33% 16.70% 19.17%</td>
</tr>
<tr>
<td>SR ( (w^* \mid r) )</td>
<td>0.27 0.27 0.26 0.24</td>
<td>0.27 0.27 0.29 0.29</td>
</tr>
</tbody>
</table>

Remark 30 In this numerical example, the impact of ESG preferences is low because the assets have similar financial characteristics: same Sharpe ratio and same cross-correlation values. This explains that the optimized portfolios are different, but their Sharpe ratios are very close. Nevertheless, the expected return is always lower when implementing an ESG strategy.

Risk premium The market total wealth \( W \) is equal to \( \int W_j \, d\omega_j \). Let \( \omega_j = W_j / W \) be the market share of the economic agent \( j \). His amount \( W_{i,j} \) invested in stock \( i \) is equal to \( W_{i,j} = w^*_{i,j} W_j = w^*_{i,j} \omega_j W \). The total dollar amount invested in stock \( i \) is then equal to

\[
W_i = \int_j W_{i,j} \, d\omega_j = \int_j w^*_{i,j} \omega_j W \, d\omega_j
\]

\( ^{10}\)In what follows, we are seeing that it is not always the case since it depends on the sign of the aggregate ESG preference \( w_m \mathcal{G} \) where \( w_m \) is the market portfolio.
Let \( w_m = (w_{1,m}, \ldots, w_{n,m}) \) be the market portfolio. We have:

\[
  w_{i,m} = \frac{W_i}{W} = \int_j w^*_i \omega_j \, dj
\]

and \( \int_j \omega_j \, dj = 1 \). Pástor et al. (2021) deduce that the market clearing condition satisfies:

\[
  w_m = \int_j \omega_j w^*_j \, dj
  = \int_j \omega_j \Gamma_j \Sigma^{-1} (\pi + \gamma_j b_j) \, dj
  = \int_j \omega_j \Gamma_j \Sigma^{-1} (\pi + \gamma_j \varphi_j \mathcal{G}) \, dj
  = \left( \int_j \Gamma_j \omega_j \, dj \right) \Sigma^{-1} \pi + \left( \int_j \omega_j \Gamma_j \psi_j \, dj \right) \Sigma^{-1} \mathcal{G}
\]

where \( \psi_j = \gamma_j \varphi_j \). Let \( \Gamma_m = \int_j \Gamma_j \omega_j \, dj \) and \( \psi_m = \Gamma_m^{-1} \left( \int_j \omega_j \Gamma_j \psi_j \, dj \right) \) be the average risk tolerance and the weighted average of ESG preferences. The expression of the market portfolio is then equal to:

\[
  w_m = \Gamma_m \Sigma^{-1} \pi + \Gamma_m \psi_m \Sigma^{-1} \mathcal{G}
\]

We deduce that the asset risk premia are equal to:

\[
  \pi = \frac{1}{\Gamma_m} \Sigma w_m - \psi_m \mathcal{G}
\]
while the market risk premium is defined as:

\[ \pi_m = w_m^\top \pi \]

\[ = \frac{1}{\Gamma_m} w_m^\top \Sigma w_m - \psi_m w_m^\top G_m \]

\[ = \frac{1}{\Gamma_m} \sigma_m^2 - \psi_m G_m \]

where \( \sigma_m = \sqrt{w_m^\top \Sigma w_m} \) and \( G_m = w_m^\top G \) are the volatility and the green intensity (or greenness) of the market portfolio. On page 139 (see footnote b.), we have seen that \( \pi_{\text{capm}}^m = \Gamma_m^{-1} \sigma_m^2 \) is the risk premium deduced from the CAPM. Since \( \Gamma_m \geq 0 \) and \( \psi_m \geq 0 \), Pástor et al. (2021) notice that:

- The risk premium including the ESG sentiment is lower than the CAPM risk premium if the market ESG intensity is positive:

\[ G_m > 0 \implies \pi_m \leq \pi_{\text{capm}}^m \]

- It is greater than the CAPM risk premium if the market ESG intensity is negative:

\[ G_m < 0 \implies \pi_m \geq \pi_{\text{capm}}^m \]

- The gap \( \Delta \pi_m^{\text{esg}} := |\pi_m - \pi_{\text{capm}}^m| \) is an increasing function of the market ESG sentiment \( \psi_m \):

\[ \psi_m \nearrow \implies \Delta \pi_m^{\text{esg}} \nearrow \]

If we assume that \( G_m \approx 0 \), we have \( \Gamma_m = \sigma_m^2 / \pi_m \) and:

\[ \pi = \beta \pi_m - \psi_m G \]

(3.14)

because \( \beta (w_m) = (w_m^\top \Sigma w_m)^{-1} \Sigma w_m \) is the vector of asset betas with respect to the market portfolio. This is the most important result of Pástor et al. (2021). It follows that the alpha of asset \( i \) is equal to:

\[ \alpha_i = \pi_i - \beta_i \pi_m = -\psi_m G_i \]

Pástor et al. (2021) conclude that if \( \psi_m > 0 \), “green stocks have negative alphas, and brown stocks have positive alphas. Moreover, greener stocks have lower alphas.”

**Example 12** We consider Example 11. The market is made up of two long-only investors \((j = 1, 2)\): a non-ESG investor \((\varphi_1 = 0)\) and an ESG investor \((\varphi_2 > 0)\). We assume that they have the same risk tolerance \( \gamma \). We note \( W_1 \) and \( W_2 \) their financial wealth, which is entirely invested in the risky assets. We assume that \( W_1 = W_2 = 1 \).

If the market is at the equilibrium, we have to compute the market portfolio. If there is no short-selling constraint, we have seen that the weights of the tangency portfolio are equal to:

\[ w^* = \frac{\Sigma^{-1} (\mu - r \mathbf{1})}{\mathbf{1}^\top \Sigma^{-1} (\mu - r \mathbf{1})} \]

We obtain \( w^* = (15.04\%, 15.04\%, 16.65\%, 16.65\%, 18.31\%, 18.31\%) \). Since there is no short position, this is the market portfolio\(^{11}\) without ESG preferences. It follows that the optimal portfolio \( w^*_1 \) of

\(^{11}\) Otherwise, we have to solve the Markowitz QP problem subject to the constraints \( \mathbf{1}^\top w = 1 \) and \( w_i \geq 0 \).
the first economic agent is equal to $w^s$. Then, we deduce the risk-tolerance coefficient of this agent and find:

$$
\gamma_1 = \frac{1}{1^\top \Sigma^{-1} (\mu - r 1)} = 0.4558
$$

We can now compute the optimal portfolio of the second economic agent by assuming that $\gamma_2 = \gamma_1$ and considering the following optimization problem:

$$
\begin{align*}
    w^*_2 &= \arg \min \frac{1}{2} w^\top \Sigma w - \gamma_2 w^\top (\mu + \gamma_2 \varphi_2 \mathcal{G}) \\
    &\text{ s.t. } \begin{cases} 
        1^\top w = 1 \\
        w \geq 0
    \end{cases}
\end{align*}
$$

It is important to use the QP program and not the analytical formula, because the ESG-tilted returns $\mu' = \mu + \gamma_2 \varphi_2 \mathcal{G}$ may be very different from the asset returns $\mu$. In this example, the long-only market portfolio is equal to the long/short tangency portfolio because we consider a uniform correlation of 25% and a constant Sharpe ratio of 20%. The ESG preference $\varphi_2$ combined with the greenness vector $\mathcal{G}$ may dramatically change the Sharpe ratio of the assets when it is computed with the ESG-tilted returns. We obtain $w^*_2 = (18.86\%, 11.22\%, 21.33\%, 11.97\%, 23.96\%, 12.65\%)$. The market portfolio is then equal to:

$$
\begin{align*}
    w_m &= \frac{W_1}{W} w^*_1 + \frac{W_2}{W} w^*_2 \\
    &= (1 - \omega^{\text{esg}}) \cdot w^*_1 + \omega^{\text{esg}} \cdot w^*_2
\end{align*}
$$

where $W = W_1 + W_2$ and $\omega^{\text{esg}}$ is the wealth share of ESG investors. When $W_1 = W_2 = 1$, we obtain $w_m = (16.95\%, 13.13\%, 18.99\%, 14.31\%, 21.13\%, 15.48\%)$, $\mu_m = 7.86\%$ and $\sigma_m = 14.93\%$. It follows that the beta values are equal to $\beta = (1.15, 1.05, 1.04, 0.95, 0.95, 0.86)$. We deduce that the risk premia are $\pi = (5.58\%, 5.12\%, 5.06\%, 4.61\%, 4.62\%, 4.17\%)$. Finally, we conclude that the alpha vector expressed in bps is $\alpha = (-19.09, 26.19, -19.43, 25.84, -19.72, 25.55)$. A summary of these results is given in Table 3.5.

**Table 3.5:** Computation of alpha returns (Example 12, $n = 6$, $\rho = 25\%$)

<table>
<thead>
<tr>
<th>$i$</th>
<th>$w_i$</th>
<th>$\beta_i$</th>
<th>$\pi_i$</th>
<th>$w_i$</th>
<th>$\beta_i$</th>
<th>$\pi_i$</th>
<th>$\alpha_i$ (in bps)</th>
<th>$w_i$</th>
<th>$\beta_i$</th>
<th>$\pi_i$</th>
<th>$\alpha_i$ (in bps)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>15.04</td>
<td>1.11</td>
<td>5.39</td>
<td>18.86</td>
<td>1.17</td>
<td>5.69</td>
<td>-30</td>
<td>16.95</td>
<td>1.15</td>
<td>5.58</td>
<td>-19</td>
</tr>
<tr>
<td>2</td>
<td>15.04</td>
<td>1.11</td>
<td>5.39</td>
<td>11.22</td>
<td>0.99</td>
<td>4.80</td>
<td>58</td>
<td>13.13</td>
<td>1.05</td>
<td>5.12</td>
<td>26</td>
</tr>
<tr>
<td>3</td>
<td>16.65</td>
<td>1.00</td>
<td>4.87</td>
<td>21.33</td>
<td>1.07</td>
<td>5.18</td>
<td>-32</td>
<td>18.99</td>
<td>1.04</td>
<td>5.06</td>
<td>-19</td>
</tr>
<tr>
<td>4</td>
<td>16.65</td>
<td>1.00</td>
<td>4.87</td>
<td>11.97</td>
<td>0.88</td>
<td>4.30</td>
<td>57</td>
<td>14.31</td>
<td>0.95</td>
<td>4.61</td>
<td>26</td>
</tr>
<tr>
<td>5</td>
<td>18.31</td>
<td>0.91</td>
<td>4.43</td>
<td>23.96</td>
<td>0.98</td>
<td>4.76</td>
<td>-33</td>
<td>21.13</td>
<td>0.95</td>
<td>4.62</td>
<td>-20</td>
</tr>
<tr>
<td>6</td>
<td>18.31</td>
<td>0.91</td>
<td>4.43</td>
<td>12.65</td>
<td>0.80</td>
<td>3.87</td>
<td>56</td>
<td>15.48</td>
<td>0.86</td>
<td>4.17</td>
<td>26</td>
</tr>
</tbody>
</table>

**Remark 31** In Figure 3.7, we show the evolution of the alpha return $\alpha_i$ with respect to the market share $\omega^{\text{esg}}$ of ESG investors. It increases in absolute value because the deviation of the market portfolio including ESG preferences increases with $\omega^{\text{esg}}$. We notice that $\alpha_1 \approx \alpha_3 \approx \alpha_5$ and $\alpha_2 \approx \alpha_4 \approx \alpha_6$ because of the specification of the exercise problem. If the Sharpe ratio of assets is different and the correlation is not uniform, the alpha returns are more diffuse.
Figure 3.7: Evolution of the alpha return with respect to the market share of ESG investors (Example 12, n = 6, \( \rho = 25\% \))

Interpretation of the results  As we have already mentioned, we must differentiate expected returns and realized returns. From a theoretical point of view, there is a scientific consensus that the risk premium of brown assets is positive, implying that the risk premium of green assets is negative (Zerbib, 2019; Ben Slimane et al., 2020; Bolton and Kacperczyk, 2021). This is because there is a systematic market risk when investing in brown assets due to several factors, including carbon pricing, regulation, reputational, asset stranding and climate hedging risks. Moreover, it is obvious that high demand for green assets from ESG investors lowers their expected returns. However, we must be careful because the positive expected excess return of brown assets does not necessarily imply that the performance of green assets is lower than the performance of brown assets:

“In equilibrium, green assets have low expected returns because investors enjoy holding them and because green assets hedge climate risk. Green assets nevertheless outperform when positive shocks hit the ESG factor, which captures shifts in customers’ tastes for green products and investors’ tastes for green holdings.” (Pástor et al., 2021).

The important word in this quote is equilibrium, meaning that green assets have low expected returns in the long run. In this case, investors will need to earn an additional return to compensate for the risk they take when investing in brown assets. In the short term however, when the market is not at equilibrium, green assets can outperform brown assets, in particular when we observe a supply/demand imbalance.

We may wonder what does equilibrium mean? In fact, it refers to a certain long-term period. In order to quantify the long run more precisely, we consider the one-factor risk model:

\[
R_i - r = \alpha_i + \beta_i (R_m - r) + \varepsilon_i
\]
where $R_m \sim \mathcal{N}(\mu_m, \sigma_m^2)$ is the stochastic market return, $\varepsilon_i \sim \mathcal{N}(0, \tilde{\sigma}_i^2)$ is the idiosyncratic risk and $\varepsilon_i \perp \varepsilon_j$. It follows that $(R_i, R_j)$ follows a bivariate Gaussian distribution:

$$
\begin{pmatrix}
R_i \\
R_j
\end{pmatrix} = \mathcal{N}\left(\begin{pmatrix}
\mu_i \\
\mu_j
\end{pmatrix},
\begin{pmatrix}
\sigma_i^2 & \sigma_{i,j} \\
\sigma_{i,j} & \sigma_j^2
\end{pmatrix}\right)
$$

where $\mu_i = r + \alpha_i + \beta_i (\mu_m - r)$, $\sigma_i^2 = \beta_i^2 \sigma_m^2 + \tilde{\sigma}_i^2$ and $\sigma_{i,j} = \beta_i \beta_j \sigma_m^2$. We deduce that $R_i - R_j = \mathcal{N}(\mu_{i-j}, \sigma_{i-j}^2)$ where:

$$
\mu_{i-j} = (\alpha_i - \alpha_j) + (\beta_i - \beta_j) (\mu_m - r)
$$

and:

$$
\sigma_{i-j}^2 = (\beta_i - \beta_j)^2 \sigma_m^2 + \tilde{\sigma}_i^2 + \tilde{\sigma}_j^2
$$

Let us assume that the two assets have the same systematic risk: $\beta_i = \beta_j$. We obtain:

$$
R_i - R_j = \mathcal{N}(\alpha_i - \alpha_j, \tilde{\sigma}_i^2 + \tilde{\sigma}_j^2)
$$

In the standard CAPM, the alpha returns are equal to zero and we deduce that:

$$
\Pr\{R_i < R_j\} = \frac{1}{2}
$$

If two assets have the same systematic risk, the probability that one asset underperforms the other is equal to 50%. Let us now take into account the ESG preferences by considering that asset $i$ is the green asset and asset $j$ is the brown asset. The one-year underperformance probability becomes:

$$
p_u(\Delta \alpha) = \Pr\{R_i < R_j\} = \Phi\left(\frac{\alpha_j - \alpha_i}{\sqrt{\tilde{\sigma}_i^2 + \tilde{\sigma}_j^2}}\right) > \frac{1}{2}
$$

because we have $\Delta \alpha = \alpha_j - \alpha_i > 0$. We can extend this formula to a greater holding period than one year. If we assume that the dynamics of asset returns are Brownian motions, we obtain:

$$
p_u(\Delta \alpha, t) = \Phi\left(\frac{(\alpha_j - \alpha_i) \sqrt{t}}{\sqrt{\tilde{\sigma}_i^2 + \tilde{\sigma}_j^2}}\right)
$$

where $t$ is the holding period. Using this formula, we can find the holding period to achieve a given underperformance probability $p_u$:

$$
t(\Delta \alpha, p_u) = \frac{\left(\tilde{\sigma}_i^2 + \tilde{\sigma}_j^2\right)}{(\alpha_j - \alpha_i)^2} \Phi^{-1}(p_u)^2
$$

In Figure 3.8, we report the relationship between $\Delta \alpha$ and the underperformance probability $p_u(\Delta \alpha, t)$ for several values of the holding period\textsuperscript{12}. For plausible values of $\Delta \alpha$ (less than 200 bps), we notice that the probability is lower than 55% for a one-year holding period. It increases until 70% for a ten-year time period, which is not very high. Therefore, it follows that the values of $t(\Delta \alpha, p_u)$ are very high at the asset level. Let us now consider the same exercise at the portfolio level. We consider an equally-weighted portfolio of 500 green assets and 500 brown assets. Results are given in the bottom/right panel. If the alpha difference is equal to 40 bps, an underperformance probability of 90% is achieved in two years.

\textsuperscript{12}We assume a typical value of 10% for the idiosyncratic volatility: $\tilde{\sigma}_i = \tilde{\sigma}_j = 10\%$. 

\textit{Handbook of Sustainable Finance}
Remark 32 All these results show that the term equilibrium refers to long holding periods. At the asset level, alpha returns require at least ten years to observe a significant difference. At the portfolio level, a three-year holding period is necessary for the materialization of alpha returns.

We may wonder whether the PST model considers the ESG risk premium or it is more adapted to assess the green risk premium. Indeed, the sustainable characteristic of the firm $i$ is measured by a non-random metric $G_i$. For instance, $G_i$ may correspond to the carbon footprint or the green intensity\textsuperscript{13} of the firm. If we apply this model with ESG characteristics, $G_i$ is the ESG score $S_i$ of the firm. In this case, assuming that all investors have the same view on the ESG score is a strong hypothesis. In particular, we have already seen that there are a high divergence between ESG scoring models (Berg et al., 2022). In this context, the original formulation of the PST model is certainly more adapted to assess the climate risk premium than the ESG risk premium.

Extension of the model

ESG uncertainty The previous issue has been solved by Avramov et al. (2022) (hereafter, ACLT model), who analyze the impact of ESG score uncertainty on the ESG risk premium. For that, they assume that ESG scores are stochastic and may be correlated to asset excess returns:

$$
\left( \tilde{R} \quad \tilde{S} \right) \sim \mathcal{N} \left( \begin{pmatrix} \pi \\ \mu_s \end{pmatrix}, \begin{pmatrix} \Sigma & \Sigma_{\pi,s} \\ \Sigma_{s,\pi} & \Sigma_s \end{pmatrix} \right)
$$

where $\tilde{R}$ and $\tilde{S}$ are the random vectors of excess returns and ESG scores. It follows that $\tilde{b}_j = \varphi_j \tilde{S}$ is stochastic and not constant. Using Equation (3.12), we deduce that the expected utility of the

\textsuperscript{13}Measured by the green revenue share for instance.
economic agent $j$ is equal to:

\[ \mathbb{E} \left[ \mathcal{U} \left( \hat{W}_j, w_j \right) \right] = e^{-\Gamma_j (1+r)} \mathbb{E} \left[ \exp \left( -\Gamma_j w_j^\top \left( \hat{R} + \psi_j \mathcal{S} \right) \right) \right] \]

where $\psi_j = \gamma_j \varphi_j$. Since we have $\hat{R} + \psi_j \mathcal{S} \sim \mathcal{N} (\hat{\mu}_j, \hat{\Sigma}_j)$ where $\hat{\mu}_j = \pi + \psi_j \mu_s$ and $\hat{\Sigma}_j = \Sigma + \psi_j^2 \Sigma_s + 2\psi_j \Sigma \rho, s$, a new expression of the expected utility is:

\[ \mathbb{E} \left[ \mathcal{U} \left( \hat{W}_j, w_j \right) \right] = e^{-\Gamma_j (1+r)} \exp \left( -\Gamma_j w_j^\top \hat{\mu}_j + \frac{1}{2} \Gamma_j^2 w_j^\top \hat{\Sigma}_j w_j \right) \]

The first-order condition is equal to $-\Gamma_j \hat{\mu}_j + \Gamma_j^2 \Sigma_j w_j = 0$, implying that the optimal portfolio is:

\[ w_j^* = \Gamma_j \Sigma_j^{-1} \hat{\mu}_j = \Gamma_j \Sigma_j^{-1} (\pi + \psi_j \mu_s) \]

This is exactly the same expression than Equation (3.13) where the asset covariance matrix $\Sigma$ is replaced by the augmented covariance matrix $\hat{\Sigma}$ and the greenness vector $\mathcal{G}$ is equal to the vector $\mu_s$ of expected ESG scores. Avramov et al. (2022) introduce the matrix $\Omega_j = \Sigma_j^{-1} - \Sigma^{-1}$ and rewrite the optimal solution as follows:

\[ w_j^* = \underbrace{\Gamma_j \Sigma_j^{-1} (\pi + \psi_j \mu_s)}_{\text{PST solution}} + \underbrace{\Gamma_j^{-1} \Omega_j (\pi + \psi_j \mu_s)}_{\text{ESG uncertainty}} \]

Therefore, the optimal portfolio is made up of two components. The first one is the optimal portfolio of the PST model. The second component is another portfolio due to the uncertainty on ESG scores. The two portfolios have the same expression, except that the second portfolio depends on the matrix $\Omega_j$ and not the covariance matrix $\Sigma$. Using market clearing conditions, Avramov et al. (2022) derive the CAPM-like relationship:

- If there is no ESG uncertainty ($\mathcal{S} = \mu_s$ and $\Sigma_s = 0$), the vector of risk premia is given by:

\[ \begin{align*}
\pi_{\text{esg}} &= \beta \pi_m - \psi_m (\mu_s - \beta \mathcal{S}_m) \\
\pi_{\text{capm}} &= \psi_m (\mu_s - \beta \mathcal{S}_m)
\end{align*} \]

where:

\[ \begin{align*}
\pi_m &= \frac{1}{\Gamma_m} \sigma_m^2 - \psi_m \mathcal{S}_m \\
\sigma_m^2 &= w_m^\top \Sigma w_m \\
\beta &= \Sigma w_m \\
\mathcal{S}_m &= w_m^\top \mu_s
\end{align*} \]

Here, $\pi_m$, $\sigma_m$ and $\mathcal{S}_m$ are the risk premium, the volatility and the ESG score of the market portfolio $w_m$, and $\beta$ is the vector of beta coefficients. $\Gamma_m$ and $\psi_m$ are the aggregate risk tolerance and ESG preference across the investors:

\[ \begin{align*}
\Gamma_m &= \frac{\int_j \omega_j \Gamma_j dj}{\int_j \omega_j dj} = \frac{\int_j \omega_j \Gamma_j dj}{\psi_m} = \frac{\int_j \omega_j \gamma_j \psi_j dj}{\Gamma_m} \\
\psi_m &= \frac{\int_j \omega_j \Gamma_j \psi_j dj}{\int_j \omega_j \Gamma_j dj}
\end{align*} \]

The authors retrieve the formula (3.14) when the market is ESG neutral\footnote{Pástor et al. (2021) assume that $\mathcal{G}_m = 0$ and find that $\pi = \beta \pi_m - \psi_m \mathcal{G}$.}.
• If there is an uncertainty on ESG scores ($\mathcal{S} \neq \mu_s$ and $\Sigma_s \neq 0$), the vector of risk premia becomes:

$$\tilde{\pi}^{\text{esg}} = \tilde{\beta} \tilde{\pi}_m - \psi_m \left( \tilde{\mu}_s - \tilde{\beta} \tilde{S}_m \right)$$

$$= \beta \pi_m + \left( \tilde{\beta} - \beta \right) \pi_m - \psi_m \left( \tilde{\mu}_s - \tilde{\beta} \tilde{S}_m \right)$$

where $\beta$ and $\psi_m$ are the values defined previously and:

$$\begin{align*}
\tilde{\pi}_m &= \frac{1}{\Gamma_m} \tilde{\sigma}^2_m - \psi_m \tilde{S}_m \\
\tilde{\sigma}^2_m &= w^\top \Sigma_m w_m \\
\tilde{\beta} &= \frac{\tilde{\Sigma}_m w_m}{\psi_m \mu_s} \\
\tilde{\mu}_s &= \frac{\psi_m \mu_s}{\Sigma_m w_m} \\
\tilde{S}_m &= w^\top \mu_s
\end{align*}$$

Here, $\tilde{\pi}_m$, $\tilde{\sigma}_m$ and $\tilde{S}_m$ are the risk premium, the volatility and the ESG score of the market portfolio $w_m$, $\tilde{\beta}$ is the vector of effective beta coefficients, and $\tilde{\mu}_s$ is the vector of modified average ESG scores. These quantities depend on $\tilde{\Sigma}_m$ and $\Psi_m$:

$$\begin{align*}
\tilde{\Sigma}_m &= \left( \int_j \omega_j \Gamma_j \Sigma^{-1}_j \Gamma^\top_j \right)^{-1} \\
\Psi_m &= \left( \int_j \omega_j \Gamma_j \Sigma^{-1}_j \Gamma^\top_j \right)^{-1} \int_j \omega_j \Gamma_j \Sigma^{-1}_j \psi_j \, dj
\end{align*}$$

The relationship $\tilde{\pi}^{\text{esg}} = \tilde{\beta} \tilde{\pi}_m - \psi_m \left( \tilde{\mu}_s - \tilde{\beta} \tilde{S}_m \right)$ obtained with ESG uncertainty is very close to the equilibrium formula $\pi^{\text{esg}} = \beta \pi_m - \psi_m \left( \mu_s - \beta \Sigma \mu_s \right)$ obtained without ESG uncertainty. In fact, the ESG uncertainty changes the risk perception of the investors. Therefore, the ESG-tilted covariance matrix $\tilde{\Sigma}_j = \Sigma + \psi_2^2 \Sigma_s + 2 \psi_2 \Sigma_{\pi,s}$ is no longer equal to the asset covariance matrix $\Sigma$. It impacts the quantities related to the market portfolio.

In order to better understand the impact of ESG uncertainty on the alpha returns, Avramov et al. (2022) consider the special case in which agents have homogeneous preferences ($\gamma_j = \gamma$, $\varphi_j = \varphi$) and the same wealth ($W_j = 1$), the covariance matrix of the ESG score is diagonal ($\Sigma_s = \text{diag}(\sigma^2_{s,1}, \ldots, \sigma^2_{s,n_s})$) and the returns are independent from the ESG scores ($\Sigma_{\pi,s} = 0$). They deduce that $\Gamma_m = \gamma$, $\psi_m = \gamma \varphi$, $\tilde{\Sigma}_m = \Sigma + \psi_2^2 \Sigma_s$, $\Psi_m = \psi I_n$, $\sigma_m^2 = \sigma^2_{m,s} + \psi_2^2 \sigma^2_{s,m}$, $\sigma^2_s = w^\top \Sigma w_m$, $\sigma^2_{s,m} = w^\top \Sigma w_m$, $\tilde{\mu}_s = \mu_s$ and $\tilde{S}_m = w^\top \mu_s$. The vector of the effective beta is equal to:

$$\tilde{\beta} = \frac{\sigma^2_{m,s}}{\sigma^2_m} \beta + \psi^2 \frac{\sigma^2_s}{\sigma^2_m} \beta_s$$

$$= \beta + \psi^2 \frac{\sigma^2_s}{\sigma^2_m} (\beta_s - \beta)$$

where:

$$\beta_s = \frac{\Sigma_s w_m}{\sigma^2_s}$$
Avramov et al. (2022) find that:

$$\tilde{\alpha}_{\text{esg}} = \tilde{\pi}_{\text{esg}} - \beta \pi_m$$

$$= \psi \frac{\sigma^2}{\sigma^2_m} (\beta_s - \beta) \pi_m - \psi_m \left( \mu_s - \left( \beta + \psi \frac{\sigma^2}{\sigma^2_m} (\beta_s - \beta) \right) \tilde{S}_m \right)$$

$$= \psi \frac{\sigma^2}{\sigma^2_m} (\beta_s - \beta) \left( \pi_m + \psi_m \tilde{S}_m \right) - \psi_m \left( \mu_s - \beta \tilde{S}_m \right)$$

If we consider the asset $i$, we obtain:

$$\beta_{i,s} = \frac{w_{i,m}}{\sigma^2_{i,s}}$$

$\beta_{i,s}$ increases with the volatility $\sigma_{i,s}$ of the score $S_i$. We deduce that:

$$\frac{\partial \tilde{\alpha}_{i}}{\partial \sigma_{i,s}} > 0$$

This implies that alpha increases with ESG uncertainty. The authors also study the impact of ESG uncertainty on the demand and test the model using the standard deviations from ESG rating agencies as a proxy for ESG uncertainty. Their conclusion is the following:

“In equilibrium, the market premium increases and demand for stocks declines under ESG uncertainty. In addition, the CAPM alpha and effective beta both rise with ESG uncertainty and the negative ESG-alpha relation weakens.” Avramov et al. (2022, page 642).

Example 13 We consider an investment universe of four assets. Their expected returns are equal to 5%, 6%, 7% and 8% while their volatilities are equal to 15%, 20%, 30% and 30%. The correlation matrix of asset returns is given by the following matrix:

$$C = \begin{pmatrix}
100% & 10% & 100% \\
10% & 100% & 40% \\
40% & 60% & 100% \\
50% & 40% & 80% \\
50% & 40% & 80% & 100%
\end{pmatrix}$$

The risk-free return is set to 2%. The average ESG scores are respectively equal to +3%, −2%, +1% and −1%, whereas the standard deviation of ESG score is the same for all the assets and is equal to 20%. We assume that the ESG preference $\varphi$ of the long-only investor is equal to 0.50 while his risk tolerance corresponds to the market risk tolerance.

We first begin by computing the market risk tolerance $\gamma_m = (1^T \Sigma^{-1} (\mu - r1))^{-1} = 0.4654$ and the weights of the market portfolio:

$$w_m = \gamma_m \Sigma^{-1} (\mu - r1) = \begin{pmatrix}
50.08% \\
49.98% \\
-22.52% \\
23.47%
\end{pmatrix}$$

Then, we consider the following optimization problem:

$$w^* (\psi, \mu_s, \Sigma_s) = \arg \min \frac{1}{2} w^T (\Sigma + \psi^2 \Sigma_s) w - \gamma_m (\mu + \psi \mu_s)$$

s.t. \(1^T w = 1, w \geq 0\)
where $\Sigma_s = 4\% \times I$, $\mu_s = (3\%, -2\%, 1\%, -1\%)$ and $\psi = \gamma_m \varphi = 0.4954 \times 0.50 = 0.2327$. In order to decompose the risk premium of the long-only ESG investor, we compute the long-only portfolio $w^*(0, \mathbf{0}_n, \mathbf{0}_{n,n})$, the long-only portfolio without ESG uncertainty $w^*(\psi, \mu_s, \mathbf{0}_{n,n})$ and the long-only portfolio with ESG uncertainty $w^*(\psi, \mu_s, \Sigma_s)$. For each portfolio, we compute the beta coefficient $\beta (w^*(\psi, \mu_s, \Sigma_s) | w_m)$ with respect to the market portfolio. We deduce the risk premium $\pi (w^*(\psi, \mu_s, \Sigma_s)) = \beta (w^*(\psi, \mu_s, \Sigma_s) | w_m) \cdot \pi_m$ where $\pi_m = \mu (x_m) - r$. We obtain the following decomposition:

$$
\pi (w^*(\psi, \mu_s, \Sigma_s)) = \pi (w_m) + \\
\left\{ \begin{array}{l}
\pi (w^*(0, \mathbf{0}_n, \mathbf{0}_{n,n})) - \pi (w_m) + \\
\pi (w^*(\psi, \mu_s, \mathbf{0}_{n,n})) - \pi (w^*(0, \mathbf{0}_n, \mathbf{0}_{n,n})) + \\
\pi (w^*(\psi, \mu_s, \Sigma_s)) - \pi (w^*(\psi, \mu_s, \mathbf{0}_{n,n})) \\
\end{array} \right.
$$

The optimal weights and risk statistics are given in Tables 3.6 and 3.7. We have:

$$
\pi (w^*(\psi, \mu_s, \Sigma_s)) = 3.74\% - 0.96 \text{ bps} - 19.80 \text{ bps} + 5.41 \text{ bps} = 3.50\%
$$

In this example, the cost of the long-only constraint is $-0.96$ bps, the ESG score alpha is equal to $-19.80$ bps whereas the ESG uncertainty alpha is equal to $5.41$ bps.

<table>
<thead>
<tr>
<th>Asset</th>
<th>$w_m$</th>
<th>$w^*(0, \mathbf{0}<em>n, \mathbf{0}</em>{n,n})$</th>
<th>$w^*(\psi, \mu_s, \mathbf{0}_{n,n})$</th>
<th>$w^*(\psi, \mu_s, \Sigma_s)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>#1</td>
<td>50.08%</td>
<td>52.00%</td>
<td>64.03%</td>
<td>61.87%</td>
</tr>
<tr>
<td>#2</td>
<td>48.98%</td>
<td>39.65%</td>
<td>31.51%</td>
<td>32.05%</td>
</tr>
<tr>
<td>#3</td>
<td>-22.52%</td>
<td>0.00%</td>
<td>0.00%</td>
<td>0.00%</td>
</tr>
<tr>
<td>#4</td>
<td>23.47%</td>
<td>8.35%</td>
<td>4.47%</td>
<td>6.09%</td>
</tr>
</tbody>
</table>

| Portfolio | $\mu (w)$ | $\sigma (w)$ | $\beta (w | w_m)$ | $\pi (w)$ | $\mathbf{S} (w)$ |
|-----------|-----------|--------------|----------------|-----------|------------------|
| $w_m$     | 5.74%     | 13.20%       | 1.0000         | 3.74%     | 0.06%            |
| $w^*(0, \mathbf{0}_n, \mathbf{0}_{n,n})$ | 5.65% | 13.33% | 0.9743 | 3.65% | 0.68% |
| $w^*(\psi, \mu_s, \mathbf{0}_{n,n})$ | 5.45% | 12.86% | 0.9214 | 3.45% | 1.25% |
| $w^*(\psi, \mu_s, \Sigma_s)$ | 5.50% | 12.99% | 0.9358 | 3.50% | 1.15% |

**Risk factor model** In the capital asset pricing model, the asset return $R_i$ satisfies the one-factor risk model:

$$
R_i - r = \alpha_i + \beta_i (R_m - r) + \varepsilon_i
$$

where $\alpha_i = 0$, $\beta_i$ is the CAPM beta of asset $i$, $R_m \sim \mathcal{N} (\mu_m, \sigma_m^2)$ is the market return, $\varepsilon_i \sim \mathcal{N} (0, \sigma_i^2)$ is the residual. Moreover, we have $\varepsilon_i \perp R_m$ and $\varepsilon_i \perp \varepsilon_j$. In matrix form, we obtain:

$$
R = r + \beta (R_m - r) + \varepsilon
$$

*Handbook of Sustainable Finance*
where \( R \sim \mathcal{N}(\mu, \Sigma) \), \( \varepsilon = (\varepsilon_1, \ldots, \varepsilon_n) \sim \mathcal{N}(0, D) \) and \( D = \text{diag}(\sigma_1^2, \ldots, \sigma_n^2) \). We deduce that:

\[
\mu = \mathbb{E}[R] = r + \beta (\mu_m - r)
\]

or:

\[
\pi = \mu - r = \beta \pi_m
\]

It follows that:

\[
R - \mu = \beta (R_m - \mu_m) + \varepsilon
\]

Therefore, the expression of the covariance matrix is:

\[
\Sigma = \mathbb{E} \left[ (R - \mu)(R - \mu)^\top \right] = \mathbb{E} \left[ \beta (R_m - \mu_m) + \varepsilon \right] \left[ \beta (R_m - \mu_m) + \varepsilon \right]^\top + 2 \beta (R_m - \mu_m) \varepsilon^\top = \sigma_m^2 \beta \beta^\top + D
\]

When we introduce ESG preferences, we obtain a two-factor model:

\[
R = r + \beta (R_m - r) + \beta_{\text{esg}} R_{\text{esg}} + \varepsilon
\]

where \( R \sim \mathcal{N}(\mu, \Sigma) \), \( R_m \sim \mathcal{N}(\mu_m, \sigma_m^2) \) is the market return, \( \varepsilon = (\varepsilon_1, \ldots, \varepsilon_n) \sim \mathcal{N}(0, D) \) and \( D = \text{diag}(\tilde{\sigma}_1^2, \ldots, \tilde{\sigma}_n^2) \). Here, \( R_{\text{esg}} \sim \mathcal{N}(\mu_{\text{esg}}, \sigma_{\text{esg}}^2) \) is the return of the ESG portfolio \( w_{\text{esg}} \propto \Sigma^{-1} \mu_s \), which is a zero-beta strategy (Pástor et al., 2021):

\[
\beta^\top w_{\text{esg}} = 0
\]

This is why we assume that \( R_{\text{esg}} \perp R_m \) and \( R_{\text{esg}} \perp \varepsilon \). We deduce that:

\[
\mu = r + \beta (\mu_m - r) + \beta_{\text{esg}} \mu_{\text{esg}}
\]

or:

\[
\pi = \beta \pi_m + \beta_{\text{esg}} \mu_{\text{esg}}
\]

For the covariance matrix, we obtain:

\[
\Sigma = \sigma_m^2 \beta \beta^\top + \sigma_{\text{esg}}^2 \beta_{\text{esg}} \beta_{\text{esg}}^\top + D
\]

Even if the ESG portfolio has a zero-return \((\mu_{\text{esg}} = 0)\), we notice that it may have a big impact on the structure of the covariance matrix.

**Remark 33** The CAPM and ESG coefficients \( \beta_i \) and \( \beta_{\text{esg}} \) do not have the same status. Indeed, we generally assume that \( \beta_i \geq 0 \). Otherwise, the asset risk premium is negative: \( \pi_i = \beta_i \pi_m \). Moreover, the CAPM average beta \( \bar{\beta} \) is close to 1 because the beta of the market portfolio is equal to 1:

\[
\beta(w_m) = 1 \iff \frac{\sum_i w_{i,m} \bar{\beta}_i}{\sum_i w_{i,m}} = 1 \iff \frac{\sum_i w_{i,m} \beta_{\text{esg}}}{\sum_i w_{i,m}} = 1 \iff \sum_i w_{i,m} \beta_i = 1
\]
In practice, we assume that $\beta_i \in [0, 3]$ in the equity market. This is not the case of the ESG factor because the ESG factor is a zero-beta long/short portfolio. This means that $\beta_{i, \text{esg}}$ can be positive and negative. In practice, the ESG factor\(^1\) is built such that $\beta_{i, \text{esg}} \in [-1, 1]$.

In order to measure the impact of ESG on the covariance matrix, we compare the one- and two-factor models. The expression of the asset variance are respectively $\sigma_i^2 (\text{capm}) = \sigma_m^2 \beta_i^2 + \tilde{\sigma}_i^2$ for the one-factor model and $\sigma_i^2 (\text{esg}) = \sigma_m^2 \beta_i^2 + \sigma_{\text{esg}}^2 \beta_{i, \text{esg}}^2 + \tilde{\sigma}_i^2$ for the two factor model. We deduce that:

$$\sigma_i^2 (\text{esg}) - \sigma_i^2 (\text{capm}) = \sigma_{\text{esg}}^2 \beta_{i, \text{esg}}^2 \geq 0$$

From a theoretical point of view, the introduction of the ESG factor increases asset volatilities. The reason lies in the fact that a new risk is priced in by the market. From a practical point of view, the impact may be lower:

$$\sigma_i^2 (\text{esg}) - \sigma_i^2 (\text{capm}) \leq \sigma_{\text{esg}}^2 \beta_{i, \text{esg}}^2$$

because the idiosyncratic volatility in the two-factor model may be reduced. Indeed, we can assume that the ESG factor may capture a part of the CAPM residual risk. If we focus on the correlation, we obtain:

$$\rho_{i,j} (\text{esg}) = \frac{\sigma_m \beta_i \beta_j + \sigma_{\text{esg}} \beta_{i, \text{esg}} \beta_{j, \text{esg}}}{\sigma_i (\text{esg}) \sigma_j (\text{esg})}$$

and:

$$\rho_{i,j} (\text{esg}) - \rho_{i,j} (\text{capm}) = \left( \frac{1}{\sigma_i (\text{esg}) \sigma_j (\text{esg})} - \frac{1}{\sigma_i (\text{capm}) \sigma_j (\text{capm})} \right) \sigma_m \beta_i \beta_j + \underbrace{\frac{\sigma_{\text{esg}} \beta_{i, \text{esg}} \beta_{j, \text{esg}}}{\sigma_i (\text{esg}) \sigma_j (\text{esg})}}_{\text{not signed}}$$

We have two effects:

1. Since asset volatilities increase, the contribution of the CAPM covariance factor $\beta_i \beta_j$ in the two factor model decreases.

2. The second component depends on the sign of the two ESG beta coefficients. If $\beta_{i, \text{esg}}$ and $\beta_{j, \text{esg}}$ are both positive or negative, the contribution is positive, otherwise it is negative. This implies that the ESG factor increases the correlation between ESG-friendly (or green) assets. The correlation also increases between ESG-unfriendly (or brown) assets. However, the correlation is decreases between a green asset and a brown asset.

Example 14 We consider an investment universe, which is made up of five assets. Their market beta is respectively equal to 0.9, 0.8, 1.2, 0.7 and 1.3 whereas their specific volatility is 4%, 12%, 5%, 8% and 5%. The market portfolio volatility is equal to 25%. Concerning the ESG factor, we have $\sigma_{\text{esg}} = 10\%$ whereas the ESG sensitivity values are set to $-0.5$, 0.7, 0.2, 0.9 and $-0.3$.

The covariance matrices are reported in Tables 3.8 and 3.9. We verify that asset volatilities have increased with the two-factor model: $\sigma_i (\text{esg}) > \sigma_i (\text{capm})$. We notice that most of correlations have decreased except the cross-correlation $\rho_{2,4}$ between the second and fourth assets. These assets

\(^1\)Since the ESG factor is long/short, we can always scale its volatility by leveraging or deleveraging.
have the largest ESG sensitivities: \( \beta_{2,\text{esg}} = 0.7 \) and \( \beta_{4,\text{esg}} = 0.9 \). The cross-correlation \( \rho_{1,5} \) is not reduced although we have \( \beta_{1,\text{esg}} = -0.5 \) and \( \beta_{3,\text{esg}} = -0.3 \). In fact, the product \( \beta_{1,\text{esg}}\beta_{3,\text{esg}} \) is not enough large to compensate the increase of the volatilities: \( \sigma_{1,\text{esg}} - \sigma_{1,\text{capm}} = 54 \) bps and \( \sigma_{5,\text{esg}} - \sigma_{5,\text{capm}} = 14 \) bps.

Table 3.8: CAPM covariance matrix (Example 14)

<table>
<thead>
<tr>
<th>Asset</th>
<th>( \sigma_i ) (in %)</th>
<th>( \rho_{i,j} ) (in %)</th>
</tr>
</thead>
<tbody>
<tr>
<td>#1</td>
<td>22.85</td>
<td>100.00</td>
</tr>
<tr>
<td>#2</td>
<td>23.32</td>
<td>84.43</td>
</tr>
<tr>
<td>#3</td>
<td>30.41</td>
<td>97.12</td>
</tr>
<tr>
<td>#4</td>
<td>19.24</td>
<td>89.54</td>
</tr>
<tr>
<td>#5</td>
<td>32.88</td>
<td>97.31</td>
</tr>
</tbody>
</table>

Table 3.9: Two-factor covariance matrix (Example 14)

<table>
<thead>
<tr>
<th>Asset</th>
<th>( \sigma_i ) (in %)</th>
<th>( \rho_{i,j} ) (in %)</th>
</tr>
</thead>
<tbody>
<tr>
<td>#1</td>
<td>23.39</td>
<td>100.00</td>
</tr>
<tr>
<td>#2</td>
<td>24.35</td>
<td>72.85</td>
</tr>
<tr>
<td>#3</td>
<td>30.48</td>
<td>93.27</td>
</tr>
<tr>
<td>#4</td>
<td>21.24</td>
<td>70.18</td>
</tr>
<tr>
<td>#5</td>
<td>33.02</td>
<td>96.61</td>
</tr>
</tbody>
</table>

We consider the portfolio \( w = \vartheta \Sigma^{-1} \eta \) where \( \eta \) is a \( n \times 1 \) vector and \( \vartheta = 1/ (\mathbf{1}^\top \Sigma^{-1} \eta) \) is the scalar such that \( \mathbf{1}^\top w = 1 \). Using results in Box 3.3, we deduce that:

\[
\begin{align*}
    w &= \vartheta D^{-1} \eta - \vartheta M^{-1} \eta \\
    &= \vartheta D^{-1} \eta - \vartheta \omega_1 \tilde{\beta} \tilde{\beta}^\top \eta - \vartheta \omega_2 \tilde{\beta}_{\text{esg}} \tilde{\beta}_{\text{esg}}^\top \eta + \vartheta \omega_3 \left( \tilde{\beta}_{\text{esg}} \tilde{\beta} + \tilde{\beta}_{\text{esg}}^\top \right) \eta \\
    &= \vartheta \left( D^{-1} - \omega_1 \tilde{\beta} \tilde{\beta}^\top \right) \eta + \vartheta \omega_3 \left( \tilde{\omega}_3 \tilde{\beta}_{\text{esg}} \tilde{\beta} + \omega_3 \tilde{\beta}_{\text{esg}} \tilde{\beta}_{\text{esg}}^\top - \omega_2 \tilde{\beta}_{\text{esg}} \tilde{\beta}_{\text{esg}}^\top \right) \eta
\end{align*}
\]

Therefore, we can derive analytical formulas for GMV \((\eta = 1)\), MVO \((\eta = \gamma \mu)\) and tangency \((\eta = \mu - r \mathbf{1})\) portfolios. For instance, if we consider the minimum variance portfolio, Roncalli et al. (2020) showed that:

\[
\omega_{i,\text{gmv}} = \frac{\sigma^2 (\omega_{\text{gmv}})}{\sigma_i^2} \max \left( 1 - \frac{\beta_i}{\beta^*} - \frac{\beta_{i,\text{esg}}}{\beta_{i,\text{esg}}^*}, c \right)
\]

where \( c = -\infty \) if there is no constraint and \( c = 0 \) in the no short-selling case. Since the mean of beta coefficients is close to one, \( \beta^* \) is positive, implying that the asset weight is a decreasing function of the asset beta. Therefore, the minimum variance portfolio is a low-beta strategy. The impact of the ESG factor is more complex because the mean of ESG beta coefficients is close to zero, implying that the threshold \( \beta_{i,\text{esg}}^* \) can be positive or negative. We conclude that the asset weight can be a decreasing or increasing function of the asset ESG beta.

**Example 15** We consider an investment universe, which is made up of five assets. Their market beta is respectively equal to 0.7, 0.8, 0.9, 1.2 and 1.5 whereas their specific volatility is 10%, 8%, 3%, 5% and 4%. The market portfolio volatility is equal to 25%. Concerning the ESG factor, we have \( \sigma_{\text{esg}} = 10\% \) whereas the ESG sensitivity values are set to \(-0.5, -0.7, -0.5, 0.9\) and 1.3.
## Box 3.3: One- and two-factor precision matrices

In portfolio optimization, several variables (weights, risk premium, etc.) are expressed with respect to the inverse of the covariance matrix, which is called the precision matrix. In the case of the one-factor model, we apply the Sherman-Morrison-Woodbury formula with $A = D$ and $u = v = \sigma_m \beta$, and we obtain:

$$
\Sigma^{-1} = D^{-1} - \frac{\sigma_m^2 \tilde{\beta} \tilde{\beta}^T}{1 + \sigma_m^2 \beta^T \beta} 
$$

where $\tilde{\beta}_i = \beta_i/\tilde{\sigma}_i^2$.

For the two-factor model, we use the generalized Sherman-Morrison-Woodbury formula with $A = D$, $u_1 = v_1 = \sigma_m \beta$ and $u_2 = v_2 = \sigma_{esg} \beta_{esg}$. It follows that the inverse of the covariance matrix is equal to:

$$
\Sigma^{-1} = D^{-1} - D^{-1}US^{-1}V^TD^{-1}
$$

where $U = V = (\sigma_m \beta \ \sigma_{esg} \beta_{esg})$ and:

$$
S = \begin{pmatrix}
1 + \sigma_m^2 \beta^T D^{-1} \beta & \sigma_m \sigma_{esg} \beta^T D^{-1} \beta_{esg} \\
\sigma_m \sigma_{esg} \beta^T D^{-1} \beta_{esg} & 1 + \sigma_{esg}^2 \beta_{esg}^T D^{-1} \beta_{esg}
\end{pmatrix}
$$

Roncalli et al. (2020) showed that:

$$
\Sigma^{-1} = D^{-1} - M^{-1}
$$

where:

$$
M^{-1} = \omega_1 \tilde{\beta} \tilde{\beta}^T + \omega_2 \tilde{\beta}_{esg} \tilde{\beta}_{esg}^T - \omega_3 \left( \tilde{\beta}_{esg} \tilde{\beta}^T + \tilde{\beta}_{esg} \tilde{\beta}_{esg}^T \right)
$$

and:

$$
\begin{align*}
\tilde{\beta}_i & = \beta_i/\tilde{\sigma}_i^2 \\
\tilde{\beta}_{i,esg} & = \beta_{i,esg}/\tilde{\sigma}_{i,esg}^2 \\
\omega_0 & = 1 + \sigma_m^2 \beta^T \beta + \sigma_{esg}^2 \beta_{esg}^T \beta_{esg} + \sigma_m^2 \sigma_{esg}^2 \left( \tilde{\beta}^T \beta \right) \left( \tilde{\beta}_{esg} \beta_{esg}^T \right) - \left( \tilde{\beta}^T \beta_{esg} \right)^2 \\
\omega_1 & = \omega_0^{-1} \sigma_m^2 \\
\omega_2 & = \omega_0^{-1} \sigma_{esg}^2 \\
\omega_3 & = \omega_0^{-1} \sigma_m^2 \sigma_{esg}^2 \left( \tilde{\beta}^T \beta_{esg} \right)
\end{align*}
$$

*See Appendix A.1.1 on page 570.

In Tables 3.10 and 3.11, we report the weights of the GMV and long-only MV portfolios and compare the allocation between the one- and two-factor models. If we consider Example 14, adding the ESG factor increases (resp. decreases) the weights of assets with negative (resp. positive) values of $\beta_{i,esg}$. The reason lies in the fact that the threshold $\beta_{esg}^*$ is positive. In the case of Example 15, $\beta_{esg}^*$ is equal to $-3.5677$ for the GMV portfolio and $-7.5752$ for the long-only MV portfolio. The relationship between $\beta_{i,esg}$ and $\omega_{i,gmv}$ becomes more complex. Indeed, the long exposure condition is $\beta_i/\beta^* + \beta_{i,esg}/\beta_{esg}^* \leq 1$. If $\beta_i \leq \beta^*$, $\omega_{i,gmv}$ may be positive if $\beta_{i,esg}$ is greater than the bound.
\( \beta_{e\text{sg}} (1 - \beta_i/\beta^*) \), which is negative. Therefore, both positive and negative values of \( \beta_{i, e\text{sg}} \) can lead to a long exposure. If \( \beta_i \geq \beta^* \), the bound is positive and only an asset with a positive ESG sensitivity has a positive weight.

Table 3.10: Minimum variance portfolios (Example 14)

<table>
<thead>
<tr>
<th>Asset</th>
<th>( \beta_i )</th>
<th>( \beta_{i, e\text{sg}} )</th>
<th>One-factor</th>
<th>Two-factor</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>GMV</td>
<td>MV</td>
</tr>
<tr>
<td>#1</td>
<td>0.90</td>
<td>-0.50</td>
<td>147.33%</td>
<td>0.00%</td>
</tr>
<tr>
<td>#2</td>
<td>0.80</td>
<td>0.70</td>
<td>24.67%</td>
<td>9.45%</td>
</tr>
<tr>
<td>#3</td>
<td>1.20</td>
<td>0.20</td>
<td>-49.19%</td>
<td>0.00%</td>
</tr>
<tr>
<td>#4</td>
<td>0.70</td>
<td>0.90</td>
<td>74.20%</td>
<td>90.55%</td>
</tr>
<tr>
<td>#5</td>
<td>1.30</td>
<td>-0.30</td>
<td>-97.01%</td>
<td>0.00%</td>
</tr>
<tr>
<td>( \sigma(w) )</td>
<td></td>
<td></td>
<td>11.45%</td>
<td>19.19%</td>
</tr>
<tr>
<td>( \beta(w) )</td>
<td></td>
<td></td>
<td>0.1913</td>
<td>0.7095</td>
</tr>
<tr>
<td>( \beta_{e\text{sg}}(w) )</td>
<td></td>
<td></td>
<td>0.2965</td>
<td>0.8811</td>
</tr>
<tr>
<td>( \beta^* )</td>
<td></td>
<td></td>
<td>1.0972</td>
<td>0.8307</td>
</tr>
<tr>
<td>( \beta_{e\text{sg}}^* )</td>
<td></td>
<td></td>
<td>19.7724</td>
<td>9.7394</td>
</tr>
</tbody>
</table>

Table 3.11: Minimum variance portfolios (Example 15)

<table>
<thead>
<tr>
<th>Asset</th>
<th>( \beta_i )</th>
<th>( \beta_{i, e\text{sg}} )</th>
<th>One-factor</th>
<th>Two-factor</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>GMV</td>
<td>MV</td>
</tr>
<tr>
<td>#1</td>
<td>0.70</td>
<td>-0.50</td>
<td>26.21%</td>
<td>66.96%</td>
</tr>
<tr>
<td>#2</td>
<td>0.80</td>
<td>-0.70</td>
<td>32.17%</td>
<td>33.04%</td>
</tr>
<tr>
<td>#3</td>
<td>0.90</td>
<td>-0.50</td>
<td>166.32%</td>
<td>0.00%</td>
</tr>
<tr>
<td>#4</td>
<td>1.20</td>
<td>0.90</td>
<td>-7.55%</td>
<td>0.00%</td>
</tr>
<tr>
<td>#5</td>
<td>1.50</td>
<td>1.30</td>
<td>-117.15%</td>
<td>0.00%</td>
</tr>
<tr>
<td>( \sigma(w) )</td>
<td></td>
<td></td>
<td>8.10%</td>
<td>19.69%</td>
</tr>
<tr>
<td>( \beta(w) )</td>
<td></td>
<td></td>
<td>0.0899</td>
<td>0.7330</td>
</tr>
<tr>
<td>( \beta_{e\text{sg}}(w) )</td>
<td></td>
<td></td>
<td>-2.7786</td>
<td>-0.5661</td>
</tr>
<tr>
<td>( \beta^* )</td>
<td></td>
<td></td>
<td>1.1664</td>
<td>0.8462</td>
</tr>
<tr>
<td>( \beta_{e\text{sg}}^* )</td>
<td></td>
<td></td>
<td>-3.5677</td>
<td>-7.5752</td>
</tr>
</tbody>
</table>

Remark 34 The previous examples illustrate that the global minimum variance portfolio can have a positive or negative ESG beta. In fact, it depends on the correlation between CAPM betas and ESG betas. Generally, the GMV portfolio has a positive ESG beta if there is a negative correlation between \( \beta_i \) and \( \beta_{i, e\text{sg}} \).

If the market risk and ESG factors are uncorrelated, we can assume that\(^{16} \beta^\top \beta_{e\text{sg}} \approx 0 \). If we consider mean-variance optimized portfolios, Equation (3.15) becomes:

\[
w = \vartheta \left( D^{-1} - \omega_1 \tilde{\beta} \tilde{\beta}^\top - \omega_2 \tilde{\beta}_{e\text{sg}} \tilde{\beta}_{e\text{sg}}^\top \right) \mu
\]

\(^{16}\)Otherwise, it means that green assets are generally associated to high beta assets if \( \beta^\top \beta_{e\text{sg}} > 0 \) or low beta assets if \( \beta^\top \beta_{e\text{sg}} < 0 \).
We deduce that:

\[ w_i \propto \omega \frac{\mu_i}{\sigma_i^2} - \omega \beta_i \frac{\hat{\beta}_i}{\sigma_i^2} - \omega \beta_{esg} \frac{\beta_{esg}}{\sigma_i^2} \]

where:

\[
\begin{align*}
\omega_\eta &= 1 + \sigma_m^2 \tilde{\beta}^\top \beta + \sigma_{esg}^2 \tilde{\beta}_{esg} \beta_{esg} \geq 0 \\
\omega_\beta &= \sigma_m^2 \left( 1 + \sigma_{esg}^2 \tilde{\beta}_{esg} \beta_{esg} \right) \sum_{j=1}^n \frac{\beta_j \mu_j}{\sigma_j^2} \geq 0 \\
\omega_{\beta_{esg}} &= \sigma_{esg}^2 \left( 1 + \sigma_m^2 \tilde{\beta}^\top \beta \right) \sum_{j=1}^n \frac{\beta_{esg} \beta_{esg}}{\sigma_j^2} \leq 0
\end{align*}
\]

We deduce that \( w_i \) is an increasing function of \( \mu_i \) and a decreasing function of \( \beta_i \) and \( \tilde{\sigma}_i \). Like the minimum variance portfolio, \( w_i \) can be a decreasing or increasing function of \( \beta_i \), \( esg \) because \( \omega_{\beta_{esg}} \) can be positive or negative.

### 3.1.3 ESG efficient frontier

Pedersen et al. (2021) propose an extension of the Markowitz optimization model by considering ESG preferences (hereafter, PFP model). Even if the model settings are similar, the PFP model slightly differs from the PST model, because it is more focused on the efficient frontier.

#### Model settings

The investment universe is made up of \( n \) assets. We have \( \tilde{R} = R - r \sim \mathcal{N}(\pi, \Sigma) \). The assets have an ESG score given by \( S = (S_1, \ldots, S_n) \). Let \( w = (w_1, \ldots, w_n) \) be the portfolio of the investor. His initial wealth is \( W \) whereas his terminal wealth is given by \( \tilde{W} = (1 + r + w^\top \tilde{R}) W \). The model uses the mean-variance utility function, which is tilted by the ESG score of the portfolio:

\[
U(\tilde{W}, w) = \mathbb{E}[\tilde{W}] - \frac{\bar{\gamma}}{2} \text{var}(\tilde{W}) + \zeta(S(w)) W
\]

\[
= \left( 1 + r + w^\top \pi - \frac{\bar{\gamma}}{2} w^\top \Sigma w + \zeta \left( w^\top S \right) \right) W
\]

where \( \zeta \) is a function that depends on the investor. Optimizing the utility function is equivalent to find the mean-variance-esg optimized portfolio:

\[
w^* = \arg \max \ w^\top \pi - \frac{\bar{\gamma}}{2} w^\top \Sigma w + \zeta \left( w^\top S \right) \]

s.t. \( 1^\top w = 1 \)

Let \( \sigma(w) = \sqrt{w^\top \Sigma w} \) and \( S(w) = w^\top S \). The optimization problem can be decomposed as follows:

\[
w^* = \arg \left\{ \max_{\mathcal{S}} \left\{ \max_{\sigma} \left\{ \max_{w} \{ f(w; \pi, \Sigma, \mathcal{S}) \quad \text{s.t.} \quad w \in \Omega(\sigma, \mathcal{S}) \} \right\} \right\} \right\}
\]  \hspace{1cm} (3.16)

where:

\[
f(w; \pi, \Sigma, \mathcal{S}) = w^\top \pi - \frac{\bar{\gamma}}{2} \sigma^2(w) + \zeta(S(w))
\]

and:

\[
\Omega = \left\{ w \in \mathbb{R}^n : 1^\top w = 1, \sigma(w) = \bar{\sigma}, S(w) = \mathcal{S} \right\}
\]
The optimal portfolio

We consider the first optimization sub-problem, which is a $\sigma - S$ problem:

$$w^* (\sigma, S) = \arg \max w^\top \pi$$

subject to

$$\begin{cases}
1^\top w = 1 \\
\sigma (w) = \sqrt{w^\top \Sigma w} = \bar{\sigma} \\
S (w) = w^\top S = \bar{S}
\end{cases}$$

Pedersen et al. (2021) rewrite the last two equations as $w^\top \Sigma w - \bar{\sigma}^2 = 0$ and $w^\top (S - \bar{S}1) = 0$ because $1^\top w = 1$. Therefore, the Lagrange function is:

$$L (w; \lambda_1, \lambda_2) = w^\top \pi + \lambda_1 \left( w^\top \Sigma w - \bar{\sigma}^2 \right) + \lambda_2 \left( w^\top (S - \bar{S}1) \right)$$

The first-order condition is:

$$\frac{\partial L (w; \lambda_1, \lambda_2)}{\partial w} = \pi + 2\lambda_1 \Sigma w + \lambda_2 (S - \bar{S}1) = 0$$

We deduce that the optimal portfolio is given by:

$$w = -\frac{1}{2\lambda_1} \Sigma^{-1} (\pi + \lambda_2 (S - \bar{S}1))$$

The second constraint $w^\top (S - \bar{S}1) = 0$ implies that:

$$(*) \iff (S - \bar{S}1)^\top \frac{1}{2\lambda_1} \Sigma^{-1} (\pi + \lambda_2 (S - \bar{S}1)) = 0$$

$$\iff \lambda_2 = -\frac{(S - \bar{S}1)^\top \Sigma^{-1} \pi}{(S - \bar{S}1)^\top \Sigma^{-1} (S - \bar{S}1)}$$

$$\iff \lambda_2 = \frac{S^\top \Sigma^{-1} S - 2S^\top (1^\top \Sigma^{-1} S) + S^2 (1^\top \Sigma^{-1} 1)}{C_{1,s} \bar{S} - C_{s,s}}$$

where $C_{x,y}$ is the compact notation for $x^\top \Sigma^{-1} y - C_{1,x} = 1^\top \Sigma^{-1} \pi$, $C_{s,\pi} = S^\top \Sigma^{-1} \pi$, $C_{s,s} = S^\top \Sigma^{-1} S$, $C_{1,s} = 1^\top \Sigma^{-1} S$ and $C_{1,1} = 1^\top \Sigma^{-1} 1$. Using the first constraint $w^\top \Sigma w - \bar{\sigma}^2 = 0$, we deduce that:

$$\bar{\sigma}^2 = -\frac{1}{2\lambda_1} w^\top \Sigma \Sigma^{-1} (\pi + \lambda_2 (S - \bar{S}1))$$

$$= -\frac{1}{2\lambda_1} \left( w^\top \pi + \lambda_2 w^\top (S - \bar{S}1) \right)$$

$$= -\frac{1}{2\lambda_1} w^\top \pi$$

$$= \frac{1}{4\lambda_1^2} \pi^\top \Sigma^{-1} (\pi + \lambda_2 (S - \bar{S}1))$$

---

17 This last constraint $1^\top w = 1$ is not used in the sequel, implying that the proportion of the wealth invested in the risk-free asset is equal to $w_r = 1 - 1^\top w$. 

Handbook of Sustainable Finance
The first Lagrange coefficient is then equal to:

\[ \lambda_1 = -\frac{1}{2\bar{\sigma}} \sqrt{\pi^\top \Sigma^{-1} \pi + \lambda_2 (\pi^\top \Sigma^{-1} S - \bar{S} (\pi^\top \Sigma^{-1} 1))} \]

\[ = -\frac{1}{2\bar{\sigma}} \sqrt{C_{\pi,\pi} - \frac{(C_{1,\pi} S - C_{s,\pi})^2}{C_{s,s} - 2C_{1,s} S + C_{1,1} S^2}} \]

where \( C_{\pi,\pi} = \pi^\top \Sigma^{-1} \pi \).

Pedersen et al. (2021) notice that the optimal portfolio is the product of the volatility \( \bar{\sigma} \) and the vector \( \varrho (\bar{S}) \):

\[ w^*(\bar{\sigma}, \bar{S}) = -\frac{1}{2\lambda_1} \Sigma^{-1} (\pi + \lambda_2 (S - \bar{S} 1)) \]

\[ = \bar{\sigma} \cdot \varrho (\bar{S}) \]

where:

\[ \varrho (\bar{S}) = \frac{1}{\lambda_1} \Sigma^{-1} (\pi + \lambda_2 (S - \bar{S} 1)) \]

and:

\[ \lambda_1' = \sqrt{C_{\pi,\pi} - \frac{(C_{1,\pi} S - C_{s,\pi})^2}{C_{s,s} - 2C_{1,s} S + C_{1,1} S^2}} \]

**Example 16** We consider an investment universe of four assets. Their expected returns are equal to 6\%, 7\%, 8\% and 10\% while their volatilities are equal to 15\%, 20\%, 25\% and 30\%. The correlation matrix of asset returns is given by the following matrix:

\[
\begin{pmatrix}
100\% & 20\% & 30\% & 40\%\\
20\% & 100\% & 50\% & 60\%\\
30\% & 50\% & 100\% & 70\%\\
40\% & 60\% & 70\% & 100\%
\end{pmatrix}
\]

The risk-free rate is set to 2\%. The ESG score vector is \( S = (3\%, 2\%, -2\%, -3\%) \).

We obtain \( C_{1,\pi} = 2.4864, C_{s,\pi} = 0.0425, C_{s,s} = 0.1274, C_{1,s} = 1.9801, C_{1,1} = 64.1106 \) and \( C_{\pi,\pi} = 0.1193 \). If we target \( \bar{\sigma} = 20\% \) and \( \bar{S} = 1\% \), we deduce that \( \lambda_1 = -0.8514 \) and \( \lambda_2 = -0.1870 \). The optimal portfolio is then:

\[ w^*(\bar{\sigma}, \bar{S}) = \begin{pmatrix}
59.31\% \\
29.52\% \\
21.76\% \\
20.72\%
\end{pmatrix} \]

It follows that the portfolio is leveraged since we have \( w_r = 1 - \mathbf{1}^\top w = -31.31\% \). We verify that \( \sqrt{w^*(\bar{\sigma}, \bar{S})^\top \Sigma w^*(\bar{\sigma}, \bar{S})} = 20\% \) and \( \left( w^*(\bar{\sigma}, \bar{S})^\top \bar{S} \right)/ \left( \mathbf{1}^\top w^*(\bar{\sigma}, \bar{S}) \right) = 1\% \). We also notice that:

\[ \varrho (\bar{S}) = \begin{pmatrix}
2.9657 \\
1.4759 \\
1.0881 \\
1.0358
\end{pmatrix} \]

and verify that \( w^*(\bar{\sigma}, \bar{S}) = \bar{\sigma} \cdot \varrho (\bar{S}) \). The portfolio is then leveraged when \( \bar{\sigma} \geq 1/(\mathbf{1}^\top \varrho (\bar{S})) = 17.75\% \).
The Sharpe ratio of the optimal portfolio

Let us rewrite the first-order condition as:

\[
\begin{align*}
(*) & \iff \pi + 2\lambda_1 \Sigma w + \lambda_2 (S - \bar{S}1) = 0 \\
& \iff w^\top \pi + 2\lambda_1 w^\top \Sigma w + \lambda_2 w^\top (S - \bar{S}1) = 0 \\
& \iff w^\top \pi + 2\lambda_1 \sigma^2 = 0 \\
& \iff \lambda_1 = -\frac{1}{2} \frac{w^\top \pi}{\sigma^2} \\
& \iff \lambda_1 = -\frac{1}{2} \frac{\text{SR}(w \mid r)}{\bar{\sigma}}
\end{align*}
\]

We deduce that the Sharpe ratio of the optimal portfolio \( w^* (\bar{\sigma}, \bar{S}) \) is equal to:

\[
\text{SR}(w^* (\bar{\sigma}, \bar{S}) \mid r) = \sqrt{C_{\pi, \pi} - \frac{(C_{1, \pi} S - C_{s, \pi})^2}{C_{s, s} - 2C_{1, s} S + C_{1, 1} S^2}} = \text{SR}(S \mid \pi, \Sigma, S)
\]

Therefore, it depends on the asset parameters \( \pi, \Sigma, S \), the ESG objective \( S \) of the investor, but not the volatility target \( \bar{\sigma} \).

Using Example 16, we deduce that the Sharpe ratio of the optimal portfolio \( w^* (20\%, 1\%) \) is equal to 0.3406. More generally, we verify that \( \text{SR}(w^* (\bar{\sigma}, \bar{S}) \mid r) \) does not depend on the value \( \bar{\sigma} \). For instance, we have \( \text{SR}(w^* (\bar{\sigma}, -3\%) \mid r) = 0.2724 \), \( \text{SR}(w^* (\bar{\sigma}, -2\%) \mid r) = 0.2875 \), \( \text{SR}(w^* (\bar{\sigma}, -1\%) \mid r) = 0.3052 \), \( \text{SR}(w^* (\bar{\sigma}, 0\%) \mid r) = 0.3242 \), \( \text{SR}(w^* (\bar{\sigma}, 1\%) \mid r) = 0.3406 \), \( \text{SR}(w^* (\bar{\sigma}, 2\%) \mid r) = 0.3443 \), and \( \text{SR}(w^* (\bar{\sigma}, 3\%) \mid r) = 0.3221 \). In Figure 3.9, we report the relationship between the target value \( S \) and the Sharpe ratio \( \text{SR}(w^* (\bar{\sigma}, \bar{S}) \mid r) \).

The ESG-SR frontier

Since the objective function is equal to:

\[
f(w^* (\bar{\sigma}, S) ; \pi, \Sigma, S) = \left( \frac{w^* (\bar{\sigma}, S)^\top \pi}{\bar{\sigma}} \right) \bar{\sigma} - \frac{\bar{\gamma}}{2} \bar{\sigma}^2 + \zeta(S)
\]

the \( \sigma \)-problem becomes:

\[
\max_{\bar{\sigma}} \left\{ \max_w \left\{ f(w; \pi, \Sigma, S) \right\} \mid w \in \Omega(\bar{\sigma}, S) \right\} = \max_{\bar{\sigma}} \left\{ \text{SR}(S \mid \pi, \Sigma, S) \bar{\sigma} - \frac{\bar{\gamma}}{2} \bar{\sigma}^2 + \zeta(S) \right\}
\]

The first-order condition is \( \text{SR}(\bar{S} \mid \pi, \Sigma, S) - \bar{\gamma} \bar{\sigma} = 0 \) or \( \bar{\sigma} = \bar{\gamma}^{-1} \text{SR}(\bar{S} \mid \pi, \Sigma, S) \), and we have:

\[
f(w^* (\bar{\sigma}, S) ; \pi, \Sigma, S) = \bar{\gamma}^{-1} \text{SR}^2(\bar{S} \mid \pi, \Sigma, S) - \frac{1}{2} \bar{\gamma}^{-1} \text{SR}^2(\bar{S} \mid \pi, \Sigma, S) + \zeta(S)
\]

\[
= \frac{1}{2} \bar{\gamma}^{-1} \left( \text{SR}^2(S \mid \pi, \Sigma, S) + 2\bar{\gamma} \zeta(S) \right)
\]

We conclude that the \( S \)-problem becomes:

\[
S^* = \arg \max_S \left\{ \text{SR}^2(S \mid \pi, \Sigma, S) + 2\bar{\gamma} \zeta(S) \right\} \quad (3.17)
\]
and the optimal portfolio is:

\[ w^* = w^*(\sigma^*, S^*) \]

where \( S^* \) is the solution of the \( S \)-problem and \( \sigma^* = \tilde{\gamma}^{-1} \text{SR}(S^* | \pi, \Sigma, S) \). Pedersen et al. (2021) distinguish three groups of investors:

- **Type-U** or ESG-unaware investors have no ESG preference and do not use the information of ESG scores;
- **Type-A** or ESG-aware investors have no ESG preference, but they use the ESG scores to update their views on the risk premia;
- **Type-M** or ESG-motivated investors have ESG preferences, implying that they would like to have a high ESG score.

Type-U investors hold the same portfolio, which is the standard tangency portfolio computed without the information of ESG scores:

\[ w^*_U = \frac{\Sigma_{\pi}^{-1}}{1^\top \Sigma_{\pi}^{-1}} \]

Type-A investors choose the optimal portfolio with the highest Sharpe ratio. This is equivalent to set \( \zeta(s) = 0 \) in Equation (3.17) and we note \( S^*_A \) the optimal ESG score. Finally, type-M investors choose an optimal portfolio on the ESG-SR efficient frontier, which has an ESG score greater than the optimal ESG score: \( S^*_M \geq S^*_A \). In this case, we have \( \text{SR}(S^*_M | \pi, \Sigma, S) \leq \text{SR}(S^*_A | \pi, \Sigma, S) \). Therefore, type-M investors reduce their Sharpe ratio in order to reach a better ESG score. While the optimal portfolio is the same for all type-A investors, it is different for two type-M investors who do not have the same risk-aversion coefficient \( \tilde{\gamma} \) and the same ESG utility function \( \zeta(s) \).
Figure 3.10: Optimal portfolio for type-U investors (Example 16)

Figure 3.11: Optimal portfolio for type-A investors (Example 16)
Figure 3.12: Optimal portfolio for type-M investors when $\zeta(s) = s$ (Example 16)

Figure 3.13: Optimal portfolio for type-M investors when $\zeta(s) = 0.2\sqrt{\max(s, 0)}$ (Example 16)
We consider Example 16. We compute the optimal portfolio for type-U investors. In this case, the previous analysis is not necessarily since the optimal portfolio is the traditional tangency portfolio. In the case of type-A investors, we must find the portfolio corresponding to the maximal Sharpe ratio of the ESG-SR efficient frontier (Figure 3.11). For type-M investors, we first compute the function $\xi(\mathcal{S})$:

$$\xi(\mathcal{S}) = \text{SR}^2(\mathcal{S} | \pi, \Sigma, \mathcal{S}) + 2\gamma \xi(\mathcal{S})$$

Then, the optimal portfolio corresponds to the optimal ESG score that maximizes $\xi(\mathcal{S})$. Two examples are provided in Figures 3.12 and 3.13. Results are summarized in Table 3.12. For instance, if $\gamma = 1.5$ and $\xi(s) = 0.2\sqrt{\text{max}(s, 0)}$, the optimal portfolio is equal to $w^*_M = (107.2\%, 66.0\%, 6.5\%, -7.9\%)$ and its Sharpe ratio is 0.332. This portfolio is obtained for an ESG score of 2.7%.

**Table 3.12: Optimal portfolios (Example 16)**

<table>
<thead>
<tr>
<th>Statistics</th>
<th>Type-U</th>
<th>Type-A</th>
<th>Type-M</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\mathcal{S}(w^*)$</td>
<td>0.017</td>
<td>0.197</td>
<td>0.023</td>
</tr>
<tr>
<td>$\sigma(w^*)$</td>
<td>0.139</td>
<td>0.100</td>
<td>0.028</td>
</tr>
<tr>
<td>$\text{SR}(w^*</td>
<td>r)$</td>
<td>0.345</td>
<td>0.345</td>
</tr>
<tr>
<td>$w^*_1$</td>
<td>0.524</td>
<td>0.378</td>
<td>3.028</td>
</tr>
<tr>
<td>$w^*_2$</td>
<td>0.289</td>
<td>0.208</td>
<td>1.786</td>
</tr>
<tr>
<td>$w^*_3$</td>
<td>0.120</td>
<td>0.086</td>
<td>0.383</td>
</tr>
<tr>
<td>$w^*_4$</td>
<td>0.067</td>
<td>0.048</td>
<td>-0.012</td>
</tr>
<tr>
<td>$w^*_5$</td>
<td>0.000</td>
<td>0.280</td>
<td>-4.184</td>
</tr>
</tbody>
</table>

**Impact on asset returns**

Pedersen et al. (2021) use the previous framework to analyze the dynamics of asset prices. They show that the impact of ESG highly depends on the relative proportion of the three types of investors. Let $\omega^U$, $\omega^A$ and $\omega^M$ be the wealth share of type-U, type-A and type-M investors. The authors assume that the security dividend payoff is given by the vector $v = (v_1, \ldots, v_n)$ and depends on the ESG scores:

$$E[v | \mathcal{S}] = \mu + \theta(\mathcal{S} - \mathcal{S}_m)$$

where $\mathcal{S}_m$ is the ESG score of the market portfolio and the parameter $\theta$ determines how informative ESG scores are for future profits. In particular, if ESG scores are not-informative, $\theta = 0$, implying that firms with better ESG scores are more profitable on average. Pedersen et al. (2021) derive the following propositions:

- If $\omega^U = 1$ and $\omega^A = \omega^M = 0$, then unconditional expected returns are given by the CAPM:

$$E[R] - r = \beta_i(E[R_m] - r)$$

but conditional expected returns depend on the ESG scores:

$$E[R_i | \mathcal{S}] - r = \beta_i(E[R_m] - r) + \theta \frac{\mathcal{S}_i - \mathcal{S}_m}{P_i}$$

where $P_i$ is the asset price of asset $i$. Two assets with the same beta do not have necessarily the same conditional risk premium.
• If $\omega^A = 1$ and $\omega^U = \omega^M = 0$, then the informational value of ESG scores is fully incorporated into asset prices, and we have:

$$\mathbb{E} [R_i | S] - r = \tilde{\beta}_i (\mathbb{E} [R_m | S] - r)$$

where $\tilde{\beta}_i$ is the ESG-adjusted beta coefficient.

• If $\omega^M = 1$ and $\omega^U = \omega^A = 0$, then the conditional expected return is given by:

$$\mathbb{E} [R_i | S] - r = \tilde{\beta}_i (\mathbb{E} [R_m | S] - r) + \lambda_2 (S_i - S_m)$$

The best case for an ESG investor is $\omega^U = 1$ and $\omega^A = \omega^M = 0$ when all the others investors are ESG-unaware. The adjustment of market prices depends then on the growth of type-A and type-M investors. More generally, negative and/or positive alpha returns are explained by asymmetric information, supply/demand imbalance and trading motivations. Therefore, there is no obvious conclusion:

“If all types of investors exist, then several things can happen. If a security has a higher ESG score, then, everything else equal, its expected return can be higher or lower. A higher ESG score increases the demand for the stock from type-M investors, leading to a higher price and, therefore, a lower required return [...] Companies with poor ESG scores that are down-weighted by type-M investors will have lower prices and higher cost of capital. [...] Furthermore, the force that can increase the expected return is that the higher ESG could be a favorable signal of firm fundamentals, and if many type-U investors ignore this, the fundamental signal perhaps would not be fully reflected in the price [...] A future increase in ESG investing would lead to higher prices for high-ESG stocks [...]. If these flows are unexpected (or not fully captured in the price for other reasons), then high-ESG stocks would experience a return boost during the period of this repricing of ESG. If these flows are expected, then expected returns should not be affected.” (Pedersen et al., 2021).

In this context, it is difficult to predict whether ESG investing will outperform or underperform in the short run, since it depends on many factors. In particular, the PST and PFP models use the efficient market hypothesis (EMH), implying that asset prices must reflect all available information. For instance, as seen above, one consequence of EMH is that expected returns are not affected if the investment flows of ESG investing are expected. In the real life, this type of assumption is difficult to verify because we know that asset prices do not instantaneously react. Assuming that the dynamics of asset prices only depend on unexpected events in the short term also limits the validity of the theoretical analysis. At the end, asset prices are driven by trading orders whatever the real motivations of investors. These motivations can be rational or not rational, related to fundamental or extra-financial information, etc. Moreover, the PST and PFP models consider a specific trading strategy that mimics the ESG integration strategy as defined on page 38. The previous results do not necessarily hold if we consider\(^\text{18}\) a worst-in-class exclusion strategy, a best-in-class selection strategy or an ESG momentum strategy. For all these reasons, the performance of ESG investing remains an intensive debate from a professional point of view. Nevertheless, these models are very useful because they give a normative framework and help to understand the mess of empirical results.

\(^{18}\text{See for instance Zerbib (2022).}\)
3.2 Empirical results

As already said, the number of empirical research on the performance of ESG investing is impressive. Nevertheless, there is no obvious consensus, because there are so many factors that must be considered. First, ESG investing has evolved since the last thirteen years. The data are not the same — most of them didn’t exist ten years ago — the practice of ESG scoring has definitively changed over time, the use of ESG considerations is new for many investors, etc. Backtesting an ESG strategy on a long history does not make sense. Second, we can not consider that the relationship between ESG and performance is static (positive or negative). Rather, we must accept that the relationship between ESG and performance is dynamic. Sometimes, ESG may create performance, but sometimes not. It was the case in the past, it will be the case in the future. Because the relationship mainly depends on the investment and trading flows of investors. Third, the performance of ESG investing depends on the portfolio implementation. This is not the same thing to consider an exclusion filter, add an ESG score to an existing asset picking model, implement a selection screening, etc. Finally, the relationship differs because it depends on the country, the asset class, the security universe, the ESG definition, etc. Let us illustrate with some examples. When we speak about the ESG performance, do we speak about the ESG global score or one of the pillars (E, S and G)? Do we speak about specific securities such as green bonds? Do we speak about American, European, Japanese or EM assets? Since we can multiply the questions endless, we focus more on the why than the whether. Why ESG investing has created or destroyed value for a specific investment universe during a given period?

3.2.1 Equity markets

The relationship between ESG and performance has been extensively investigated in stock markets. According to Coqueret (2022, Sections 4.2-4.5, pages 51-66), we can classify them into four categories: (1) ESG improves performance, (2) ESG does not impact performance, (3) ESG is financially detrimental and (4) it depends on many factors. According to Friede et al. (2015), the first category dominates the other categories:

“ [...] The results show that the business case for ESG investing is empirically very well founded. Roughly 90% of studies find a nonnegative ESG–CFP relation. More importantly, the large majority of studies reports positive findings. We highlight that the positive ESG impact on CFP appears stable over time. Promising results are obtained when differentiating for portfolio and non-portfolio studies, regions, and young asset classes for ESG investing such as emerging markets, corporate bonds, and green real estate.” (Friede et al., 2015, page 2010).

In fact, their findings are not obvious to accept since the concept of corporate financial performance covers many dimensions and is not limited to the financial performance in the equity market. For instance, CFP can also concern the cost of capital (El Ghoul et al., 2011). Moreover, a large part of these studies focus on the G pillar (Gompers et al., 2003) or use some proxy variables other than ESG scores or ratings (Edmans, 2011). We can also find many studies, whose conclusion is more neutral or negative (Barnett and Salomon, 2006; Fabozzi et al., 2008; Hong and Kacperczyk, 2009; Johnson et al., 2009; Capelle-Blancard and Monjon, 2014; Matos, 2020).

Since these different publications, a consensus has emerged among professionals. Like other investment styles, ESG investing has its good and bad times, and the relationship between ESG and performance is not straightforward and depends on many factors. Understanding these factors is the key challenge for investors rather than having a set of strong predetermined beliefs.
Simulated results

In what follows, we summarize the results obtained by Bennani et al. (2018) and Drei et al. (2019), who analyzed the impact of ESG on three equity portfolio management approaches: active management, passive management and factor investing.

Sorted portfolios Bennani et al. (2018) use the Amundi scoring system. For each company and each date, they access the ESG global score and its three components (E, S and G). The scores are normalized sector by sector in order to obtain a z-score shape, implying that they have a range roughly between \(-3\) and \(+3\). This also means that the scores are sector-neutral and distributed as a standard Gaussian probability distribution.

Box 3.4: The method of characteristic-sorted portfolios

Portfolio sorting has been popularized by Fama and French (1993) to test the impact of characteristics in asset pricing and to identify profitable investment strategies. The underlying idea is to sort individual assets into portfolios with respect to a given variable. If each portfolio has roughly the same number of constituents and only differs in the level of the sorting variable, the differences in the performance can then be attributed to the impact of the sorting variable. Generally, each portfolio is equally- or value-weighted in order to maximize the diversification. In the univariate case, the most popular approach is the quintile method, where the breakpoints for the sorting variable correspond to the 20th, 40th, 60th and 80th percentiles.

<table>
<thead>
<tr>
<th>Asset</th>
<th>Rank</th>
<th>Portfolio</th>
<th>Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>#1 6</td>
<td>-0.3</td>
<td>6</td>
<td>Q_3  +50%</td>
</tr>
<tr>
<td>#2 5</td>
<td>0.2</td>
<td>5</td>
<td>Q_3  +50%</td>
</tr>
<tr>
<td>#3 7</td>
<td>-1</td>
<td>7</td>
<td>Q_4  +50%</td>
</tr>
<tr>
<td>#4 3</td>
<td>1.5</td>
<td>3</td>
<td>Q_2  +50%</td>
</tr>
<tr>
<td>#5 10</td>
<td>-2.9</td>
<td>10</td>
<td>Q_5  +50%</td>
</tr>
<tr>
<td>#6 4</td>
<td>0.8</td>
<td>4</td>
<td>Q_2  +50%</td>
</tr>
<tr>
<td>#7 8</td>
<td>-1.4</td>
<td>8</td>
<td>Q_4  +50%</td>
</tr>
<tr>
<td>#8 2</td>
<td>2.3</td>
<td>2</td>
<td>Q_1  +50%</td>
</tr>
<tr>
<td>#9 1</td>
<td>2.8</td>
<td>1</td>
<td>Q_1  +50%</td>
</tr>
<tr>
<td>#10 9</td>
<td>-2.2</td>
<td>9</td>
<td>Q_5  +50%</td>
</tr>
</tbody>
</table>

We consider the example below, where the sorting variable is an ESG score. Since the investment universe is made up of 10 assets, each sorted portfolio has two assets. Portfolio \(Q_1\) corresponds to the highest scores, while Portfolio \(Q_5\) corresponds to the lowest scores. Finally, we obtain \(Q_1 = (#8, #9)\), \(Q_2 = (#4, #6)\), \(Q_3 = (#1, #2)\), \(Q_4 = (#3, #7)\) and \(Q_5 = (#5, #10)\).

For building the active management strategy, the authors use the sorting portfolio method. Every quarter, they rank the stocks with respect to their score, and form five quintile portfolios \(^{19}\). Portfolio \(Q_1\) corresponds to the 20% best-ranked stocks, whereas Portfolio \(Q_5\) corresponds to the 20% worst-rated stocks. The selected stocks are then equally-weighted and each portfolio is invested the first

\(^{19}\)Given a universe of stocks, each portfolio is then composed of 20% of assets.
trading day of the quarter and is held for three months. Quarterly rebalancing is implemented in order to limit the turnover.

They consider five investment universes using the following MSCI indexes: North America, EMU, Europe-ex-EMU, Japan and World. For each universe and each quintile portfolio, they calculate the gross performance without taking into account transaction costs. By analyzing the results, the authors observe a break during the 2010–2017 study period. Typically, the first half of the period is less favorable to ESG screening than the second period. In Figure 3.14, we report their results obtained for North American stocks. During the period 2010–2013, Portfolio $Q_1$ displays a gross return of 14.6% whereas Portfolio $Q_5$ shows a gross return of 17.8%. We observe an increasing function between the return and the quintile. During this period, best-in-class stocks underperformed worst-in-class stocks. The story is different when we focus on the 2014–2017 period. Portfolio $Q_1$ displays a performance of 13.0% whereas Portfolio $Q_5$ shows a performance of 9.4%. Clearly best-in-class stocks outperformed worst-in-class stocks during this second period. If we consider individual pillars, Bennani et al. (2018) obtained very similar results in Figure 3.15. $E$, $S$ and $G$ stock picking negatively impacted performance between 2010 and 2013, whereas the impact of $E$, $S$ and $G$ stock picking on performance is positive between 2014 and 2017. During the 2014–2017 period, the environmental screening produces the best result, followed by the governance scoring. However, for the governance component, the performance difference between Portfolios $Q_1$, $Q_2$, $Q_3$ and $Q_4$ is not significant. Only Portfolio $Q_5$ underperforms substantially, meaning that worst-rated stocks are penalized, but best-rated stocks are not necessarily rewarded.

These results clearly show that ESG active management was penalized during the 2010–2013 period, whereas it created an excess performance between 2014 and 2017. In the case of the Eurozone,
the conclusion is the same for the ESG global score, and its three components. For instance, Portfolio $Q_1$ generated a return of 8.6% whereas Portfolio $Q_5$ generated a return of 10.0% between 2010 and 2013 (Figure 3.16). On the contrary, the performance was respectively 14.7% and 7.5% for Portfolios $Q_1$ and $Q_3$ during the 2014–2017 period. Therefore, the first period is characterized by a U-shape, whereas best-in-class stocks far outperformed worst-in-class stocks over the second period. We notice that the performance difference mainly concerns Portfolios $Q_1$ and $Q_5$, but not Portfolios $Q_2$, $Q_3$ and $Q_4$, implying that worst-in-class stocks are penalized and best-in-class stocks are rewarded. If we consider the individual pillars, governance is the most discriminant component (Figure 3.17). The difference between $Q_1$ and $Q_5$ Portfolios exceeds 7% during the last period. For the $E$ score, we observe a U-shape behavior between 2010 and 2013. Since 2014, the relationship between the quintile portfolios and their returns is clearly decreasing. It is less impressive than for the $G$ score, but it affects all the portfolios. The integration of the social pillar is the least convincing.

For the other investment universes, the results are more heterogeneous. In the case of the Europe-ex-EMU universe, ESG integration is country specific, meaning that the performance is highly dependent on the overweight or underweight of each country. For example, the $G$ screening largely overweighted UK stocks if we consider a $Q_1 - Q_5$ long/short portfolio. On the contrary, $E$ or $S$ screenings promote Swedish stocks. The case of Japan is puzzling. Indeed, ESG screening was less favorable during the 2014–2017 period. When we consider the universe of the MSCI World index, the results are similar to those obtained for North America and the Eurozone. These different results are summarized in Table 3.13, where we have reported the impact of ESG screening.

---

For the $G$ score, the difference mainly concerns Portfolios $Q_1$ and $Q_5$, and less so the median portfolios.
Chapter 3. Impact of ESG Investing on Asset Prices and Portfolio Returns

Figure 3.16: Annualized return of ESG-sorted portfolios (MSCI EMU, global score)

Source: Bennani et al. (2018).

Figure 3.17: Annualized return of ESG-sorted portfolios (MSCI EMU, individual pillars)

Source: Bennani et al. (2018).
(S, C, and ESG) on the returns of sorted portfolios. Again, the results illustrate the contrast between the two periods. To summarize, Bennani et al. (2018) concluded that the relationship between performance and ESG is time-varying and depend on several factors, especially the region and the ESG pillar. They also noticed that some investment universes present ESG-country biases, implying that the relationship between performance and ESG cannot be analyzed. This is the case of the MSCI Europe-ex-EMU index, but such bias is not also excluded for the MSCI World index.


<table>
<thead>
<tr>
<th>Period</th>
<th>Pillar</th>
<th>North America</th>
<th>EMU</th>
<th>Europe-ex-EMU</th>
<th>Japan</th>
<th>World</th>
</tr>
</thead>
<tbody>
<tr>
<td>2010–2013</td>
<td>ESG</td>
<td>--</td>
<td>0</td>
<td>+</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>E</td>
<td>--</td>
<td>0</td>
<td>+</td>
<td>-</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>S</td>
<td>--</td>
<td>0</td>
<td>--</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>C</td>
<td>--</td>
<td>0</td>
<td>+</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>2014–2017</td>
<td>ESG</td>
<td>++</td>
<td>0</td>
<td>--</td>
<td>+</td>
<td>++</td>
</tr>
<tr>
<td></td>
<td>E</td>
<td>++</td>
<td>0</td>
<td>--</td>
<td>+</td>
<td>++</td>
</tr>
<tr>
<td></td>
<td>S</td>
<td>+</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>+</td>
</tr>
<tr>
<td></td>
<td>C</td>
<td>+</td>
<td>++</td>
<td>0</td>
<td>+</td>
<td>++</td>
</tr>
</tbody>
</table>

Source: Bennani et al. (2018).

The study of Drei et al. (2019) is an update of the analysis of Bennani et al. (2018) when considering the recent period 2018–2019. They use exactly the same data, the same investment universes and the same methodology. Their main results are reported in Figures 3.18 and 3.19.

Box 3.5: Computing the performance of long/short portfolios

Let \( w_{\text{Long}} \) and \( w_{\text{Short}} \) be the long and short portfolio. We note \( R_t(w) \) the annualized return of the portfolio \( w \) between \( t-1 \) and \( t \). The performance of the long/short portfolio \( w_{\text{Long}} - w_{\text{Short}} \) satisfies the following definition:

\[
(1 + R_t(w_{\text{Long}})) = (1 + \alpha_t(w_{\text{Long}} - w_{\text{Short}})) \cdot (1 + R_t(w_{\text{Short}}))
\]

where \( \alpha_t(w_{\text{Long}} - w_{\text{Short}}) \) is the alpha return of \( w_{\text{Long}} - w_{\text{Short}} \). We deduce that:

\[
\alpha_t(w_{\text{Long}} - w_{\text{Short}}) = \frac{R_t(w_{\text{Long}}) - R_t(w_{\text{Short}})}{1 + R_t(w_{\text{Short}})}
\]  

Looking at the \( Q_1 - Q_5 \) long-short portfolios in North America (Figure 3.18) and the Eurozone (Figure 3.19), we can see the evolution of the integration of ESG and its pillars in both markets. In the 2010–2013 period, sustainable investors were penalized, as seen by the negative return of the \( Q_1 - Q_5 \) long-short portfolios. In the 2014–2017 period, after the radical break in ESG integration, ESG investing gained momentum and yielded positive returns on all pillars on both sides of the Atlantic. However, after eight years of parallel development, Drei et al. (2019) observed a contradictory trend in ESG investing between North America and the Eurozone between 2018 and 2019. Indeed, the last period is marked by a squeeze in alpha returns on all dimensions in North America, and even a loss on the E pillar. This loss is important because it is the first long-short portfolio with a negative return since the 2014 ESG turning point in these two investment universes. Moreover, they observe
Figure 3.18: Annualized return of long/short $Q_1 - Q_5$ sorted portfolios (MSCI North America)

Source: Drei et al. (2019).

Figure 3.19: Annualized return of long/short $Q_1 - Q_5$ sorted portfolios (MSCI EMU)

Source: Drei et al. (2019).
a performance reduction of S and G pillars during the 2018–2019 period. If we consider the global ESG score, its performance remains positive but it is divided by a factor of six compared to the 2014–2017 period. On the Eurozone side, the verdict is more positive. All long-short portfolio returns are positive. During the 2018–2019 period, E and S pillars yield even stronger returns comparatively to the previous period. The decline of the G long-short portfolio return can be partly attributed to a mean-reversion effect after an extraordinary period of impressive performance. Drei et al. (2019) concluded that the 2018–2019 period is in line with the previous period for the Eurozone investment universe since the two periods post an annualized return around 6% in the case of the global ESG score.

How to explain these different results? Bennani et al. (2018) assumed that two main effects contributed to the ESG performance from 2014 to 2017: the selection effect of ESG screening and the demand effect of ESG assets. By selection effect, we think about the direct impact of extra-financial information on stock prices. By considering other risk dimensions, the ESG investor may select corporations that are better managed from social, environmental and governance viewpoints, or may avoid corporations that present extra-financial weaknesses. The underlying idea is that sooner or later these extra-financial risks have a financial impact on the performance of the corporation. The second effect is related to the supply/demand balance. Indeed, a price is the equilibrium between the supply and the demand for this stock. Bennani et al. (2018) found that ESG investment flows that have been observed since 2014 have largely contributed to the good performance of ESG investing over the 2014–2017 period, while the contribution of the selection effect is marginal. How to explain the 2014 break? In November 2013, the Norwegian Sovereign Wealth Fund adopted a new responsible investment policy (Dimson et al., 2013). At approximately the same time, we observe a strong mobilisation of the largest European institutional investors (APG, PGGM, ERAFP, FRR, etc.), which are massively invested in European and America stocks. The good performance of ESG investing during the 2014–2017 period is mainly explained by the portfolio rebalancing of these European tier-one institutional investors. The 2018–2019 period is different. Indeed, this first mobilization is followed by another mobilization of medium (or tier-two) European institutional investors, while the implication of US investors continues to be weak. Nevertheless, this second wave of investors has a low exposure on the North-American stocks. The transatlantic divided, which was observed between 2018 and 2019, is then mainly explained by the strategic asset allocation of these tier-two institutional investors. They have rebalanced their portfolios, but the trading operations mainly concerned European stocks and not American stocks. A first explanation of the American setback can then be found in these engagement differences between European and American investors. Beside the two effects (selection effect and supply/demand balance), Drei et al. (2019) suggested that a third factor may contribute to the ESG performance: the political and regulatory environment. The bad performance of the E pillar in the US may be explained by the announced withdrawal of the United States from the Paris Climate Agreement and some of the changes at the US Environmental Protection Agency (EPA). More generally, another justification of the transatlantic divided could be the public policy of the Trump administration in terms of its ESG roadmap.

Remark 35 The original idea of the Amundi Institute studies (Bennani et al., 2018; Drei et al., 2019) was to frequently update the empirical relationship between ESG and performance. Nevertheless, the first study showed that there are country biases that are difficult to control. This is why the second study has focused on the investment universe of MSCI North American and EMU indexes,

---

21 Indeed, the annualized return was 7.9% between 2014 and 2017, compared to just 1.3% for the 2018–2019 period.
22 For instance, the Norwegian Sovereign Wealth Fund had an exposure on US stocks greater than the exposures of the three largest US pension funds (CalPERS, CalSTRS and NYSCRF).
Chapter 3. Impact of ESG Investing on Asset Prices and Portfolio Returns

Figure 3.20: The monotonous assumption of the ESG-performance relationship

(a) Return-based
(b) Risk-based
(c) Skewed-return
(d) Skewed-risk

and considered the empirical relationship ESG-performance as monotonous. For instance, if the relationship is positive, we must observe $R_t(Q_1) \geq R_t(Q_2) \geq R_t(Q_3) \geq R_t(Q_4) \geq R_t(Q_5)$, while a negative relationship implies $R_t(Q_1) \leq R_t(Q_2) \leq R_t(Q_3) \leq R_t(Q_4) \leq R_t(Q_5)$. More generally, we must observe some patterns in order to interpret the results. Some of them are given in Figure 3.20. For instance, the implementation of an ESG exclusion strategy has a return-based rationale if the relationship is positive or if portfolio $Q_5$ underperforms the other quintile portfolios. In a similar way, the implementation of an ESG selection strategy has a return-based rationale if the relationship is positive or if portfolio $Q_1$ overperforms the other quintile portfolios. However, Drei et al. (2019) noticed that most of monotonous relationships that were observed during the 2010–2017 periods were no longer valid between 2018 and 2019. For instance, they found that $R_t(Q_1) \geq R_t(Q_5)$ for the ESG global score in the Eurozone, but they also found that $R_t(Q_4) \geq R_t(Q_1)$, which is a puzzling result. This ranking disorder goes beyond the binary outcome in which $Q_1 \succ Q_5$ holds or does not. Drei et al. (2019) considered that this puzzle marked the emergence of new ESG investment strategies. The $Q_1 – Q_5$ approach is representative of a static view of ESG scores, when best-in-class stocks remain best-in-class stocks and worst-in-class stocks remain worst-in-class stocks, while playing intermediary quintiles, especially the fourth quintile, seems to be related to the strategy of ESG momentum (Figure 3.21) and a dynamic view of ESG scores. During the 2018–2019 period, ESG strategies have become more complex, and this may explain the ranking disorder. This finding is in line with the results reported by GSIA (2019). In its 2018 investment review, the organization documents that the most common way to participate in sustainable investing (as measured by assets under management allocated to each strategy) is to implement negative screening, but this approach is closely tailed by ESG integration and corporate engagement strategies. Similarly, Eurosif (2018) found similar results a year before, and stated that “the main strategy is exclusion, but in the last two years the growth rate of this strategy slowed down. In contrast, best-in-class and ESG integration have had a high
growth rate”. Investment strategies based on the dynamics of ESG ratings do not clearly correspond to negative or positive screening, but they are more related to ESG integration. In this approach, an improvement of an extra-financial criterion may lead to portfolio rebalancing, exactly as we observe for financial ratios. The convergence between the extra-financial approach and the traditional security analysis certainly increases the focus on the dynamics and momentum of ESG ratings, and not just their static level. In this context, analyzing the relationship between the performance of ESG investing and the static level of ESG scores is certainly outdated.

Figure 3.21: How to play ESG momentum?

Optimized portfolios Many institutional investors implement ESG policy through passive management. In this case, they use two techniques: exclusion and optimization. The first approach consists in reducing the universe of the stock index by excluding the worst rated stocks, and then applying a capitalization-weighted scheme to form the investment portfolio. The second approach consists in improving the score of the investment portfolio with respect to the score of the benchmark portfolio, while controlling the tracking error risk. The first solution can be approximated by using the second method, implying that optimized portfolios can be used to simulate the performance of ESG passive management. This approach has been extensively used by Bennani et al. (2018) and Drei et al. (2019).

Remark 36 Let us compare the ESG-optimized approach with the ESG-sorting method. We note \( F \) the probability distribution of the score \( S \). Portfolio \( Q_1 \) corresponds to best-in-class stocks \( \{ i \in Q_1 \iff S_i \geq F^{-1} (80\%) \} \), whereas Portfolio \( Q_5 \) corresponds to worst-in-class stocks \( \{ i \in Q_5 \iff S_i \leq F^{-1} (20\%) \} \). Moreover, the weights are uniform: \( w_i (Q_j) = \frac{1}{n} \) where \( n \) is the total number of assets in the investment universe. In the case of the ESG-optimized approach, we have \( w^* (\gamma) = \Sigma^{-1} (\gamma S + \Sigma b) \), implying that \( w^*_i (\gamma) = b_i + \gamma (\Sigma^{-1}_i S)_i \). Therefore, the benchmark weights are tilted by the inverse of the covariance matrix times the vector of ESG scores. For example, if we assume that the covariance matrix is diagonal and \( S_i \sim N (0, 1) \), we obtain:

\[
w^*_i (\gamma) = b_i + \gamma \frac{S_i}{\sigma_i^2}
\]

A positive score increases the benchmark weight whereas \( \gamma \) controls the discrepancy. If \( \gamma = 0 \), the optimal portfolio is the benchmark. When \( \gamma \) tends to \( +\infty \), the optimal weight is proportional to the score divided by the variance. If we add the long-only constraint, the optimization problem selects the stocks such that the ratio \( S_i / \sigma_i^2 \) is greater than a threshold that depends on the parameter \( \gamma \).
**Box 3.6: ESG-optimized portfolios**

We note $b$ the benchmark, $S$ the vector of ESG scores and $\Sigma$ the covariance matrix. We consider the following optimization problem:

$$w^*(\gamma) = \arg\min_{w} \frac{1}{2} \sigma^2(w \mid b) - \gamma S(w \mid b)$$

where $\sigma^2(w \mid b) = (w - b)^\top \Sigma (w - b)$ and $S(w \mid b)$ are the ex-ante tracking error variance and the ESG excess score of portfolio $w$ with respect to the benchmark $b$. Since we have:

$$S(w \mid b) = (w - b)^\top S = S(w) - S(b)$$

we obtain the following optimization function:

$$w^*(\gamma) = \arg\min_{w} \frac{1}{2} w^\top \Sigma w - w^\top (\gamma S + \Sigma b)$$

The ESG-variance efficient frontier is defined by the parametric curve $(\sigma^2(w^*(\gamma) \mid b), S(w^*(\gamma) \mid b))$ with $\gamma \geq 0$. The QP form is given by $Q = \Sigma$ and $R = \gamma S + \Sigma b$. If we target an ESG excess score, for instance $S(w \mid b) \geq \Delta S^*$, we set $\gamma = 0$ and add the inequality constraint $S^\top w \geq S(b) + \Delta S^*$. The QP form is given by $Q = \Sigma$, $R = \Sigma b$, $C = -S^\top$ and $D = -(S(b) + \Delta S^*)$. If we use the traditional long-only constraint $(1^\top w = 1$ and $w_i \geq 0)$, we have $A = 1^\top$, $B = 1$ and $w^- = 0$.

We can then compute the value of $\gamma$ in order to retrieve the stock selection given by portfolios $Q_1$, $Q_1 + Q_2$, etc. This is why ESG-optimized and ESG-sorting approaches are related and generally give similar results.

In Figure 3.22, we report the ESG-variance efficient frontier estimated by Bennani et al. (2018). It represents the relationship between the excess score and the tracking error volatility for the MSCI World universe. For example, improving the score of the index portfolio by 0.5 implies accepting a tracking error of 32 bps on average, and an excess score of 1.0 leads to a tracking error of 85 bps. Using a risk attribution analysis, the authors also show that the governance pillar generates more tracking error than the environmental and social pillars. These results mean that ESG passive management requires taking on a significant tracking error risk with respect to capitalization-weighted benchmarks.

Figure 3.24 presents the performance of ESG optimized portfolios with respect to the excess score. We notice that the integration of ESG in passive management reduced its performance between 2010 and 2013, whereas it improved its annualized return between 2014 and 2017. For instance, an excess score of 1.0 led to an excess return of $-34$ bps during the first period and +45 bps during the second period. We also notice that the relationship between excess score and excess return is not necessarily monotonous. For instance, targeting an excess score of 1.5 instead of 1.0 results in reducing the excess return from 45 bps to 19 bps in the second period. This is most likely due to the diversification effect. Indeed, by increasing the excess score, we reduce the

---

23 See Exercise 3.4.1 on page 201.

24 We recall that these studies use z-scores, meaning that the range is between $-3$ and $+3$.

25 On average, optimized portfolios with the G score have a 50% larger tracking error than with E and S scores (see Figure 3.23).
Figure 3.22: Efficient frontier of ESG-optimized portfolios (MSCI World, 2010-2017, global score)

Source: Bennani et al. (2018).

Figure 3.23: Efficient frontier of ESG-optimized portfolios (MSCI World, 2010–2017, individual pillars)

Source: Bennani et al. (2018).
Figure 3.24: Annualized excess return of ESG-optimized portfolios (MSCI World, 2010–2017, global score)

Figure 3.25: Annualized excess return of ESG-optimized portfolios (MSCI World, 2010–2013, individual pillars)

Source: Bennani et al. (2018).
Chapter 3. Impact of ESG Investing on Asset Prices and Portfolio Returns

Figure 3.26: Annualized excess return of ESG-optimized portfolios (MSCI World, 2014–2017, individual pillars)

![Graph showing annualized excess return of ESG-optimized portfolios (MSCI World, 2014–2017, individual pillars).](source)

Source: Bennani et al. (2018).

Figure 3.27: Annualized excess return in bps of ESG-optimized portfolios (MSCI North America and EMU, 2010–2017)

![Graph showing annualized excess return in bps of ESG-optimized portfolios (MSCI North America and EMU, 2010–2017).](source)

Source: Bennani et al. (2018).
number of positions in the invested portfolios. There comes a threshold where the gains from the ESG screening are offset by the losses resulting from the diversification reduction. If we consider the individual pillars, Bennani et al. (2018) retrieve the main conclusions that they have found for active management. For the MSCI World universe, all the pillars destroyed value between 2010–2013, except the environmental pillar for which results are neutral or slightly positive. This is particularly true for the governance pillar, whose underperformance is about two/three times greater the underperformance of the overall ESG score (Figure 3.25). For the 2014–2017 period, the story changes. Every score creates an outperformance, except the social pillar (Figure 3.26). If we consider the North America and Europe investment universes\textsuperscript{26}, the performance of optimized portfolios is in line with the performance of stock picking portfolios (Figure 3.27). During the 2010–2013 period, only the E score would have generated outperformance in Europe. In this region, the authors found that the performance of the ESG score was also neutral when targeting low tracking error risk (less than 60 bps) or low excess score (less than 0.8). In all other cases, we observe a negative excess return, especially in North America. Between 2014 and 2017, we obtain opposite results. All the scores generate an outperformance, except the social pillar. The results are more significant in Europe than in North America. To summarize, the two big winners were the environmental pillar in North America and the governance pillar in Europe between 2014 and 2017.

The updated study of Drei et al. (2019) has confirmed most of the results found by Bennani et al. (2018), especially the trade-off between excess score and tracking error risk, and the reversal phenomenon of the ESG-performance relationship, which is negative when targeting a high excess score. This reversal phenomenon is most likely due to the diversification effect. Indeed, by increasing the excess score, we reduce the number of positions held in the managed portfolio. Therefore, there comes a threshold where the gains from the ESG screening are offset by the losses resulting from the diversification reduction. Since the relationship between quintile portfolios and performance is not monotonous, Drei et al. (2019) noticed that the performance of ESG-optimized portfolios is less impressive between 2018 and 2019 than during the 2014–2017 period. This is why they observe a reduction in the maximum excess return. Focusing on the Eurozone investment universe, where the loss of diversification is reached faster than in North America, they conclude that “optimized portfolios generate poorer results (except for the social pillar)\textsuperscript{2}, and more generally that “risk-return profiles are less interesting than before”\textsuperscript{27}. Therefore, the dynamic view of ESG investing implies that the performance of ESG-optimized portfolios is not necessarily in line with the performance of \( Q_1 - Q_5 \) sorted portfolios, because of the impact of the other sorted portfolios, in particular the fourth quintile portfolio.

**A new risk factor?** Previously, we have seen that the long/short \( Q_1 - Q_5 \) strategy has generated a positive alpha between 2014 and 2019, whereas ESG investing has penalized ESG investors between 2010 and 2013. When we speak about alpha generation, we generally refer to factor investing. Indeed, factor investing makes the difference between the financial performance coming from systematic factors and the financial performance coming from specific factors. Said differently, factor investing makes the difference between alpha and beta returns. In factor investing, beta (or systematic) factors correspond to the common risk factors that explain a significant part of the cross-section of stock returns. Since ESG changes the landscape of asset management, we may wonder whether ESG has become a new risk factor and must be integrated into a factor investing framework, or whether it remains an alpha strategy. To answer this question, Roncalli (2020b) use the single-factor model:

\[
R_{i,t} = \alpha_{i,j} + \beta_{i,j} F_{j,t} + \epsilon_{i,t}
\]

\textsuperscript{26}Bennani et al. (2018) have merged Eurozone and Europe-ex-EMU stocks into the same investment universe because the tracking error optimization forces the portfolio to be more or less country-neutral.
where \( R_{i,t} \) is the return of stock \( i \) at time \( t \), \( F_{j,t} \) is the value of the \( j^{th} \) common risk factor at time \( t \) and \( \varepsilon_{i,t} \) is the idiosyncratic risk. The coefficients \( \alpha_{i,j} \) and \( \beta_{i,j} \) are estimated by the method of ordinary least squares. For each stock, we compute the coefficient of determination:

\[
\varrho_{i,j}^2 = 1 - \frac{\text{var}(\varepsilon_{i,t})}{\text{var}(R_{i,t})}
\]

We can then calculate the average proportion of the return variance explained by the common factor:

\[
\bar{\varrho}_j^2 = \frac{1}{n} \sum_{i=1}^{n} \varrho_{i,j}^2
\]

We consider the standard factors derived from a factor investing framework: size, value, momentum, low-volatility and quality. These factors \( F_{j,t} \) are built using the Fama-French methodology of sorted portfolios. Contrary to the academic literature, a long-only framework is used, which is the usual approach of institutional investors. This means that the factors correspond to \( Q_1 \) portfolios or best-in-class stocks. Moreover, we consider the traditional market factor, which corresponds to the capitalization-weighted portfolio. All the analyses use weekly returns. Results are given in Table 3.14. We read these figures as follows: between 2010 and 2013, the market risk factor explains 40.8% of the dispersion of North American stock returns, this figure is 39.3% if we consider the size factor, etc. We observe that ESG has been a strong contender as a standalone factor and competes with the market risk factor. On average, since 2014, the market risk factor explains 28.6% of the cross-section variance, whereas the ESG factor has an explanatory power of 27.4% in North America. In the Eurozone, these figures are respectively 36.3% and 35.3%. Moreover, it has more explanatory power than the other risk factors both in North America and the Eurozone during the two periods: 2010–2013 and 2014–2019.

Table 3.14: Results of cross-section regression with long-only risk factors (single-factor linear regression model, average \( \varrho^2 \))

| Factor | North America | | Eurozone | |
|--------|---------------|-----------------|------------------|
| Market | 40.8%         | 28.6%           | 42.8%      | 36.3%     |
| Size   | 39.3%         | 26.1%           | 37.1%      | 23.3%     |
| Value  | 38.9%         | 26.7%           | 41.6%      | 33.6%     |
| Momentum | 39.6%        | 26.3%           | 40.8%      | 34.1%     |
| Low-volatility | 35.8% | 25.1% | 38.7% | 33.4% |
| Quality | 39.1%         | 26.6%           | 42.4%      | 34.6%     |
| ESG    | 46.1%         | 27.4%           | 42.6%      | 35.3%     |

Source: Roncalli (2020b).

We now consider a multi-factor model:

\[
R_{i,t} = \alpha_i + \sum_{j=1}^{m} \beta_{i,j} F_{j,t} + \varepsilon_{i,t}
\]

where \( m \) is the number of risk factors. In this approach, we compare the CAPM or one-factor model, the standard five-factor model based on size, value, momentum, low-volatility and quality risk factors, and the six-factor model, which consists in adding the ESG factor to the universe of

---

**Handbook of Sustainable Finance**
the five alternative risk factors. In Table 3.15, we verify that the five-factor model increases the proportion of systematic risk with respect to the CAPM. For example, the CAPM and the 5F model explain respectively 28.6% and 38.4% of the cross-section variance in North America during the second period. Adding the ESG factor has a minor impact between 2014 and 2019: 39.7% versus 38.4% in North America and 45.8% versus 45.0% in the Eurozone. This means that the ESG factor does not significantly improve the five-factor model. However, if we apply statistical tests of significance to the six-factor model, we find that ESG is statistically significant in the Eurozone, but not in North America. We may conclude that ESG could be a risk factor in the Eurozone, but not in North America.

Table 3.15: Results of cross-section regression with long-only risk factors (multi-factor linear regression model, average $R^2$)

<table>
<thead>
<tr>
<th>Model</th>
<th>North America</th>
<th></th>
<th>Eurozone</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>CAPM</td>
<td>40.8%</td>
<td>28.6%</td>
<td>42.8%</td>
<td>36.3%</td>
</tr>
<tr>
<td>5F model</td>
<td>46.1%</td>
<td>38.4%</td>
<td>49.5%</td>
<td>45.0%</td>
</tr>
<tr>
<td>6F model (5F + ESG)</td>
<td>46.7%</td>
<td>39.7%</td>
<td>50.1%</td>
<td>45.8%</td>
</tr>
</tbody>
</table>

Source: Roncalli (2020b).

The previous results may be disturbing. Indeed, cross-section regressions show that ESG is a very good single factor, but the added value of ESG in a multi-factor framework is limited. The difference between the two approaches is the cross-correlation between risk factors that are taken into account into the cross-section multi-factor regression. In order to better understand these results, Roncalli (2020b) consider a factor picking (or a factor selection) approach. This approach is similar to the multi-factor approach, but a lasso penalized regression is used in place of the traditional least squares regression:

$$\{\hat{\alpha}_i, \hat{\beta}_{i,1}, \ldots, \hat{\beta}_{i,m}\} = \arg \min \left\{ \frac{1}{2} \text{var}\left(\epsilon_{i,t}\right) + \lambda \|\beta_i\|_1 \right\}$$

The advantage is that we can control the factor intensity of the multi-factor portfolio. Therefore, we obtain a factor selection procedure. Beginning with a low-factor intensity ($\lambda \approx \infty$), we can determine which risk factor is the most important. Then, we increase the factor intensity in order to establish an ordering between risk factors. When the factor intensity reaches 100% ($\lambda = 0$), we obtain the same results calculated previously with the linear regression. The results are reported in Figures 3.28 and 3.29 for the period 2014–2019. In North America, we notice that quality is the first selected factor, followed by ESG, momentum, value, and finally low-volatility. Therefore, ESG is the second selected factor in North America. Thus, ESG should be a significant factor when building a multi-factor portfolio. However, we observe that the ESG beta first increases and then decreases when we increase the factor intensity. When the factor intensity reaches 100%, ESG represents a low exposure. Therefore, a part of the ESG exposure has been replaced by an exposure to other risk factors. This means that ESG has a high contribution in a low-diversified portfolio, but it is somewhat redundant in an already well-diversified portfolio. In the case of the Eurozone, we face a different situation. ESG is the first selected factor and remains an important factor even if we increase the factor intensity. For instance, it is more significant than momentum and low-volatility.

These different results (single-factor, multi-factor and factor picking) show that ESG investing remains an alpha strategy in North America. It may have generated outperformance, but the ESG risk factor cannot explain the dispersion of stock returns better than the standard five-factor
Figure 3.28: Factor picking (MSCI North America, 2014–2019, global score)

Source: Roncalli (2020b).

Figure 3.29: Factor picking (MSCI EMU, 2014–2019, global score)

Source: Roncalli (2020b).
risk model. This implies that introducing ESG in a multi-factor portfolio, which is already well-diversified, adds very little value. This is clearly the definition of an alpha strategy. On the contrary, we notice that ESG is a significant factor in a Eurozone multi-factor portfolio. We may then improve the diversification of multi-factor portfolios by integrating an ESG risk factor. As such, in the Eurozone, it seems that an ESG strategy is more a beta strategy than an alpha strategy.

Remark 37 These last observations can be related to the development of factor investing, for example low-volatility and quality risk factors (Roncalli, 2017). Low-volatility strategies have been known for many years, but they primarily emerged in the asset management industry between 2003 and 2004 after the dot.com bubble. Initially, low-volatility strategies were considered as alpha strategies. After the 2008 Global Financial Crisis, they were massively implemented, thereby becoming beta strategies. The case of the quality anomaly is similar. This shows that there is not a clear boundary between alpha and beta. When an alpha strategy is massively invested, it has an enough impact on the structure of asset prices to become a risk factor. The alpha/beta status of ESG strategies is related to investment flows. Indeed, an alpha strategy becomes a common market risk factor once it represents a significant part of investment portfolios and explains the cross-section dispersion of asset returns. This may explain that ESG is more a risk factor in the Eurozone than in North America.

Table 3.16: Performance of ESG equity indexes (MSCI World, 2010–2022)

<table>
<thead>
<tr>
<th>Year</th>
<th>Return (in %)</th>
<th>Alpha (in bps)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>BM ESG SRI ESG SRI</td>
<td></td>
</tr>
<tr>
<td>2010</td>
<td>11.8 10.7 10.6 −109 −114</td>
<td></td>
</tr>
<tr>
<td>2011</td>
<td>−5.5 −5.4 −5.5 12 2</td>
<td></td>
</tr>
<tr>
<td>2012</td>
<td>15.8 14.5 13.2 −135 −258</td>
<td></td>
</tr>
<tr>
<td>2013</td>
<td>26.7 27.6 27.4 89 71</td>
<td></td>
</tr>
<tr>
<td>2014</td>
<td>4.9 4.9 3.9 −6 −102</td>
<td></td>
</tr>
<tr>
<td>2015</td>
<td>−0.9 −1.1 −1.6 −23 −71</td>
<td></td>
</tr>
<tr>
<td>2016</td>
<td>7.5 7.3 7.7 −26 18</td>
<td></td>
</tr>
<tr>
<td>2017</td>
<td>22.4 21.0 23.6 −142 124</td>
<td></td>
</tr>
<tr>
<td>2018</td>
<td>−8.7 −7.8 −6.7 94 199</td>
<td></td>
</tr>
<tr>
<td>2019</td>
<td>27.7 28.2 29.8 48 209</td>
<td></td>
</tr>
<tr>
<td>2020</td>
<td>15.9 15.3 19.9 −61 396</td>
<td></td>
</tr>
<tr>
<td>2021</td>
<td>21.8 24.7 27.0 288 523</td>
<td></td>
</tr>
<tr>
<td>2022</td>
<td>−18.1 −19.6 −22.5 −143 −436</td>
<td></td>
</tr>
<tr>
<td>3Y</td>
<td>4.9 5.0 5.7 2 73</td>
<td></td>
</tr>
<tr>
<td>5Y</td>
<td>6.1 6.4 7.4 31 125</td>
<td></td>
</tr>
<tr>
<td>7Y</td>
<td>8.5 8.5 9.6 1 110</td>
<td></td>
</tr>
<tr>
<td>10Y</td>
<td>8.9 8.9 9.5 5 64</td>
<td></td>
</tr>
</tbody>
</table>

Equity indexes

Another way to illustrate that the time-varying property of the performance of ESG investing is to analyze the annualized return of equity indexes. In Table 3.16, we compare the MSCI World capitalization-weighted index (BM) with the MSCI World ESG Leaders and SRI indexes. MSCI ESG Leaders indexes target companies that have the highest ESG rated performance in each sector of the parent index. MSCI SRI indexes are designed to represent the performance of companies with high ESG ratings.

---

27. "MSCI ESG Leaders indexes target companies that have the highest ESG rated performance in each sector of the parent index. MSCI SRI indexes are designed to represent the performance of companies with high ESG ratings."
each index, we report the annualized return in % and we also compute the alpha in bps with respect to the CW parent index. For instance, the 2022 return was −18.1% for the MSCI World index (BM), −19.6% for the MSCI World ESG Leaders index and −22.5% for the MSCI World SRI index. Therefore, the alpha of ESG and SRI indexes is negative and is respectively equal to −143 and −436 bps. If we consider the last thirteen years, the benchmark index has overperformed the ESG index eight times, and the SRI index only five times. The 3Y, 5Y, 7Y and 10Y annualized returns are greater for the ESG and SRI indexes than for the BM index. These results clearly highlights that ESG investing may create alpha in some periods. Moreover, the relative performance depends on the construction of the ESG index. Indeed, we do not observe the same patterns between ESG Leaders and SRI indexes.

In Table 3.17, we confirm that the performance of ESG investing depends on several factors. For instance, the region has a significant impact. The MSCI EMU SRI index has created a positive alpha every year between 2015 and 2021 with an average of 393 bps per year. For the MSCI EM ESG Leaders index, the period of euphoria is between 2010 and 2017 with an average alpha of 423 bps per year. The choice of the ESG scoring model is another factor. Indeed, if we consider the S&P 500 ESG index, it has generated a positive alpha in 2014, 2020 and 2022 whereas the MSCI USA ESG Leaders index posted a negative alpha in these years (19 vs. −49 bps in 2014, 138 vs. −251 bps in 2020 and 43 vs. −73 bps in 2022).

Figure 3.30: Alpha return of several ESG equity indexes (in bps)

Source: MSCI, Factset & Author’s calculations.

Remark 38 In Figure 3.30, we have reported the distribution of alpha returns of ESG equity indexes over time. This perfectly illustrates that “ESG investing has its good and bad times”.

They employ a best-in-class selection approach to target the top 25% companies in each sector according to their MSCI ESG Ratings” (www.msci.com/our-solutions/indexes/esg-indexes).
<table>
<thead>
<tr>
<th>Year</th>
<th>Return</th>
<th>Alpha</th>
<th>Return</th>
<th>Alpha</th>
<th>Return</th>
<th>Alpha</th>
<th>Return</th>
<th>Alpha</th>
<th>Return</th>
<th>Alpha</th>
<th>Return</th>
<th>Alpha</th>
<th>Return</th>
<th>Alpha</th>
</tr>
</thead>
<tbody>
<tr>
<td>2010</td>
<td>4.0%</td>
<td>-0.0%</td>
<td>3.7%</td>
<td>-0.3%</td>
<td>4.0%</td>
<td>-0.0%</td>
<td>4.0%</td>
<td>-0.0%</td>
<td>4.0%</td>
<td>-0.0%</td>
<td>4.0%</td>
<td>-0.0%</td>
<td>4.0%</td>
<td>-0.0%</td>
</tr>
<tr>
<td>2011</td>
<td>14.8%</td>
<td>2.3%</td>
<td>17.0%</td>
<td>2.6%</td>
<td>11.0%</td>
<td>1.4%</td>
<td>14.8%</td>
<td>2.3%</td>
<td>14.8%</td>
<td>2.3%</td>
<td>14.8%</td>
<td>2.3%</td>
<td>14.8%</td>
<td>2.3%</td>
</tr>
<tr>
<td>2012</td>
<td>5.3%</td>
<td>-0.7%</td>
<td>4.0%</td>
<td>-0.3%</td>
<td>3.7%</td>
<td>-0.3%</td>
<td>3.7%</td>
<td>-0.3%</td>
<td>3.7%</td>
<td>-0.3%</td>
<td>3.7%</td>
<td>-0.3%</td>
<td>3.7%</td>
<td>-0.3%</td>
</tr>
<tr>
<td>2013</td>
<td>3.1%</td>
<td>0.8%</td>
<td>2.8%</td>
<td>0.9%</td>
<td>3.1%</td>
<td>0.8%</td>
<td>2.8%</td>
<td>0.9%</td>
<td>3.1%</td>
<td>0.8%</td>
<td>2.8%</td>
<td>0.9%</td>
<td>3.1%</td>
<td>0.8%</td>
</tr>
<tr>
<td>2014</td>
<td>1.8%</td>
<td>-2.8%</td>
<td>1.1%</td>
<td>-1.7%</td>
<td>3.4%</td>
<td>-1.5%</td>
<td>3.4%</td>
<td>-1.5%</td>
<td>3.4%</td>
<td>-1.5%</td>
<td>3.4%</td>
<td>-1.5%</td>
<td>3.4%</td>
<td>-1.5%</td>
</tr>
<tr>
<td>2015</td>
<td>0.9%</td>
<td>-4.1%</td>
<td>3.2%</td>
<td>-3.0%</td>
<td>1.0%</td>
<td>-3.9%</td>
<td>1.0%</td>
<td>-3.9%</td>
<td>1.0%</td>
<td>-3.9%</td>
<td>1.0%</td>
<td>-3.9%</td>
<td>1.0%</td>
<td>-3.9%</td>
</tr>
<tr>
<td>2016</td>
<td>1.1%</td>
<td>-0.7%</td>
<td>3.7%</td>
<td>-2.3%</td>
<td>1.3%</td>
<td>-0.1%</td>
<td>1.3%</td>
<td>-0.1%</td>
<td>1.3%</td>
<td>-0.1%</td>
<td>1.3%</td>
<td>-0.1%</td>
<td>1.3%</td>
<td>-0.1%</td>
</tr>
<tr>
<td>2017</td>
<td>2.1%</td>
<td>1.2%</td>
<td>2.0%</td>
<td>1.2%</td>
<td>2.1%</td>
<td>1.2%</td>
<td>2.1%</td>
<td>1.2%</td>
<td>2.1%</td>
<td>1.2%</td>
<td>2.1%</td>
<td>1.2%</td>
<td>2.1%</td>
<td>1.2%</td>
</tr>
<tr>
<td>2018</td>
<td>3.1%</td>
<td>2.8%</td>
<td>3.1%</td>
<td>2.8%</td>
<td>3.1%</td>
<td>2.8%</td>
<td>3.1%</td>
<td>2.8%</td>
<td>3.1%</td>
<td>2.8%</td>
<td>3.1%</td>
<td>2.8%</td>
<td>3.1%</td>
<td>2.8%</td>
</tr>
<tr>
<td>2019</td>
<td>4.0%</td>
<td>4.0%</td>
<td>4.0%</td>
<td>4.0%</td>
<td>4.0%</td>
<td>4.0%</td>
<td>4.0%</td>
<td>4.0%</td>
<td>4.0%</td>
<td>4.0%</td>
<td>4.0%</td>
<td>4.0%</td>
<td>4.0%</td>
<td>4.0%</td>
</tr>
<tr>
<td>2020</td>
<td>5.0%</td>
<td>5.0%</td>
<td>5.0%</td>
<td>5.0%</td>
<td>5.0%</td>
<td>5.0%</td>
<td>5.0%</td>
<td>5.0%</td>
<td>5.0%</td>
<td>5.0%</td>
<td>5.0%</td>
<td>5.0%</td>
<td>5.0%</td>
<td>5.0%</td>
</tr>
<tr>
<td>2021</td>
<td>6.0%</td>
<td>6.0%</td>
<td>6.0%</td>
<td>6.0%</td>
<td>6.0%</td>
<td>6.0%</td>
<td>6.0%</td>
<td>6.0%</td>
<td>6.0%</td>
<td>6.0%</td>
<td>6.0%</td>
<td>6.0%</td>
<td>6.0%</td>
<td>6.0%</td>
</tr>
<tr>
<td>2022</td>
<td>7.0%</td>
<td>7.0%</td>
<td>7.0%</td>
<td>7.0%</td>
<td>7.0%</td>
<td>7.0%</td>
<td>7.0%</td>
<td>7.0%</td>
<td>7.0%</td>
<td>7.0%</td>
<td>7.0%</td>
<td>7.0%</td>
<td>7.0%</td>
<td>7.0%</td>
</tr>
</tbody>
</table>

Table 3.17: Performance of ESG equity indexes

Source: MSCI, Factset & Author's calculations.
3.2.2 Fixed-income markets

Compared to stock markets, there are few studies that analyze the impact of ESG screening on fixed-income markets. For instance, Menz (2010) investigated the relationship between the valuation of Euro corporate bonds and corporate social responsibility and concluded that “CSR has apparently not yet been incorporated into the pricing of corporate bonds”. In a similar way, a neutral or slightly positive effect of socially responsible investment was demonstrated by Derwall and Koedijk (2009) when they compared the performance of SRI and conventional bond funds. This overall neutrality, sometimes associated with a lack of maturity in incorporating ESG information into the bond market, was also highlighted by Goldreyer et al. (1999), Bauer et al. (2005) and Cortez et al. (2009). In the CAPM approach, active management performance is captured by measuring the alpha. However, Lin et al. (2019) constructed industry- and credit rating-controlled quintile portfolios but found no significant evidence of ESG factor contribution to a positive alpha in the bond market. On the contrary, Oikonomou et al. (2014) found that corporate social performance is rewarded on the corporate debt market. Results of Leite and Cortez (2016) are slightly positive, but highly dependent on the country. For instance, they concluded that “French SRI bond funds match the performance of their conventional peers, German funds slightly outperform and UK funds significantly underperform conventional funds”. Polbennikov et al. (2016) also noted a slight outperformance of high ESG rated over low ESG rated bonds after controlling for varying risk exposures. More recently, Gerard (2019) and Pereira et al. (2019) found that there is no link between ESG and performance in the corporate bond markets.

Simulated results

There are three main reasons that the relationship between ESG and bond returns could be different than the relationship between ESG and stock returns:

1. The first reason concerns the sensitivity to ESG. Indeed, ESG criteria are very important for a stockholder, because ESG risks can affect the long-term business risk and can strongly impact the value of the equity. In the case of a debtholder, his main objective is to manage the default risk, which is more a short-run risk. Therefore, the concept of active ownership does not really apply to fixed-income instruments. For instance, the absence of voting rights reduces dramatically the impact of engagement policies when ESG investors focus on the bond market. From a theoretical point of view, it is then generally accepted that stockholders are more sensitive to ESG factors than bondholders. This may explain the lower integration of ESG in fixed-income markets. Other factors can explain the difference to ESG sensitivity. For instance, stock prices react faster and more sharply than bond prices to negative events, news flows and market sentiment, while bond prices are mainly driven by long-term fundamentals. Moreover, the liquidity difference between the two markets and the buy-and-hold strategy imply that equities are most commonly traded than bonds. In this context, investors may have the view that fixed-income markets do not price in ESG issues.

2. The second reason concerns the impact of ESG investment flows. In the case of stocks, they create a pressure on stock prices. In the case of bonds, we observe two effects. Investment flows can of course impact the dynamics of credit spreads and then create a pressure on bond prices, but they have also an impact on the primary market by reducing or increasing the coupon. ESG investment flows have then an effect on the carry, and a high ESG score generally implies a carry reduction because of the supply/demand balance.

3. The third reason is related to the correlation between ESG ratings and credit ratings. A
part of extra-financial information is already incorporated into credit ratings. In a bond investment universe, the conditional probability distribution of ESG scores is then different to the unconditional probability distribution of ESG scores. Most of the times, we distinguish IG and HY bonds. Since we observe a positive correlation between ESG and credit ratings, it follows that there are more worst-in-class issuers in the HY universe than in the IG universe. So, we observe a distortion of the ESG scores, which are no longer sector-neutral in fixed-income. Moreover, the average ESG-score will certainly not be equal to zero. It is positive for IG bonds and negative for HY bonds.

These several reasons explain that ESG scoring is more incorporated in equity portfolio management, while ESG integration is generally limited to exclusions in bond portfolio management. Moreover, the development of pure-play ESG securities has generally induced a segmentation in the construction of bond portfolios. On one hand, we find a core portfolio, which corresponds to a global aggregate fixed-income strategy and uses minimum ESG criteria without really promoting ESG analysis. On the other hand, a satellite portfolio is invested on green and social bonds with the goal to implement an impact investing strategy.

Sorted portfolios Ben Slimane et al. (2019b) has applied the sorted and optimized approach of Bennani et al. (2018) to the universe of bonds from the Intercontinental Exchange Bank of America Merrill Lynch large cap investment grade corporate bond index. The study period is from January

---

In Figure 3.31, we report the estimated density function of Amundi ESG $z$-scores within IG and HY universes. The empirical standard deviation of $z$-scores is equal to 1.01 whatever the bond universe. On the contrary, we find that the empirical mean is respectively equal to 0.02 and $-0.38$ for IG and HY bonds.
2010 to August 2019. Every month, they rank the bonds with respect to their ESG score, and form five quintile portfolios. Portfolio $Q_1$ corresponds to the 20% best-ranked bonds, whereas portfolio $Q_5$ corresponds to the 20% worst-rated bonds. By construction, sorted portfolios are sector-neutral. However, the authors perform some clustering because some sectors are small. Sorted portfolios are then built using the same structure of weights as the benchmark, while the selected bonds are equally-weighted within a sector. Moreover, each portfolio is rebalanced on a monthly basis, implying that the portfolio is invested the first trading day of the month and is held for the entire month. In Figure 3.32, we report the difference of returns between the best-in-class portfolio and the worst-in-class portfolio. We use two performance measures. The total return (TR) corresponds to the mark-to-market return of the portfolio, including bond price variations and coupon effects. The credit return (CR) indicates the return in excess of the total return of a risk-matched basket of governments or interest rate swaps, thus neutralizing the interest rate and yield curve risk and isolating the portion of performance attributed solely to credit and optionality risks. If we focus on the total return measure, all $Q_1 - Q_5$ EUR-denominated portfolios had a positive performance, both in 2010–2013 and 2014–2019. If we consider the credit return measure, ESG and S long/short portfolios exhibited a negative performance before 2014, whereas all the portfolios have posted a positive performance during the second period. If we consider the universe of USD-denominated investment grade corporate bonds, the worst-in-class portfolio has generally outperformed the best-in-class portfolio except for the Governance pillar between 2010 and 2013.

Figure 3.32: Annualized return in bps of the long short $Q_1 - Q_5$ strategy (IG, 2010–2019)

We can draw the following conclusions from the previous results. First, the quintile portfolios present some strong bias in terms of duration risk. This is why the results based on credit return measures are not coherent with those based on total return measures. Second, these results confirm
that the period 2014–2019 has generated a better performance in terms of ESG investing, but only for EUR-denominated corporate bonds. For USD-denominated corporate bonds, the performance remains negative. Finally, we need to be careful about the feasibility to capture the ESG alpha. For instance, if we consider the long/short $Q_1 - Q_5$ strategy, the credit return is equal to 36.8 bps during the second period. We can break down this ESG alpha into the long leg and the short leg. In Figure 3.33, we report the raw performance of sorted portfolios. The carry statistics in bps are:

<table>
<thead>
<tr>
<th>Period</th>
<th>$Q_1$</th>
<th>$Q_5$</th>
<th>$Q_1 - Q_5$</th>
</tr>
</thead>
<tbody>
<tr>
<td>2010–2013</td>
<td>175</td>
<td>192</td>
<td>-17</td>
</tr>
<tr>
<td>2014–2019</td>
<td>113</td>
<td>128</td>
<td>-15</td>
</tr>
</tbody>
</table>

Therefore, the positive credit return of the long/short $Q_1 - Q_5$ cannot be explained by the carry exposure. It is due to the mark-to-market component and the dynamics of credit spreads and bond prices. This implies that an ESG strategy has a short carry position. On the one hand, buy-and-hold ESG investors may then suffer from this structural exposure, but they can increase the credit risk of their buy-and-hold portfolio to compensate the lower carry. On the other hand, active ESG investors may overperform only if they are able to rebalance their portfolio. Liquidity issues in the corporate bond market is then a barrier to create ESG alpha in the fixed-income universe. In particular, if we impose turnover constraints when building the previous simulated portfolios, we notice a decrease of the alpha return.

![Figure 3.33: Annualized credit return in bps of ESG sorted portfolios (EUR IG, 2010–2019)](image-url)

Source: Ben Slimane et al. (2019b).
Optimized portfolios In the sorted portfolios, there is no control of the duration or the credit spread. Therefore, it is difficult to know whether the alpha return is explained by the ESG scoring or the duration/spread biases. In fact, the method of sorted portfolios is not really relevant when it is implemented in the fixed-income universe. A better method is to consider the optimization approach, when the portfolio manager imposes some constraints on the active risk that he could take with respect to the benchmark index. Ben Slimane et al. (2019b) define the active risk measure as the weighted average of the duration and credit risks (see Box 3.7). Then, they implement an optimization program, which consists in minimizing the active risk while controlling the ESG excess score of the tilted portfolios. Starting from an ESG excess score equal to zero, they progressively increase the ESG score of the optimized portfolio until they reach one. They found that the relationship between the ESG excess score and the ex-post tracking error volatility is approximately linear. On average, targeting an excess score of one requires accepting a tracking error of 25 bps.

Using the ICE (BofAML) Large Cap IG EUR Corporate Bond index, Figures 3.34 and 3.35 show the impact of the ESG integration on the excess credit return of optimized portfolios for the periods 2010–2013 and 2014–2019. During the first period, the excess return of ESG optimized portfolios is negative, meaning that ESG investors were penalized. This is particularly true when optimized portfolios targeted high excess scores. For instance, an ESG excess score of +1 has produced an underperformance of −35 bps per year. During the second period, we observe slight positive outperformance that peaks at +4 bps when the ESG tilt is set to +1. We also notice that the relationship between the ESG excess score and the excess credit return is increasing. If we now consider the individual pillars, E, S and G optimized portfolios underperform during the 2010–2013 period. Among the three pillars, environmental is the best pillar and its excess return slides down until −22 bps when the targeted excess score is set to +1. Governance is the worst pillar, and its excess return reaches −49 bps for the same tilt. After 2014, excess credit returns are between −3 and +9 bps. Social is the winning pillar and exhibits significant outperformance that peaks at +9 bps. The recent period is then more favorable to ESG investors than before 2014.

If we consider the universe of USD investment grade corporate bonds, the results are different than those obtained with EUR-denominated corporate bonds. ESG investing has not created positive alpha for the entire 2010–2019 period (see Figures 3.36 and 3.37). Nevertheless, the substantial underperformance during the 2010–2013 period has been dramatically reduced since 2014. For instance, the excess return is close to zero for social-optimized portfolios between 2014 and 2019. Another interesting remark is the behavior of the governance pillar. In many academic studies, linkage between ESG and corporate financial performance is generally justified by the governance transmission channel. The results of Ben Slimane et al. (2019a) show that the governance pillar is not necessarily the most important factor, and investing in bonds with a good governance score is not fundamentally better than using the other pillars.

Remark 39 The authors wonder if the transatlantic divide really concerns the currency of issued bonds or if it is more a regional issue. For instance, a EUR-denominated bond can be issued by an European corporate, but also by a firm which is located outside Europe. In a similar way, a USD-denominated bond can be issued by an American corporate, but also by a firm which is located outside America. Ben Slimane et al. (2019b) calculated the contribution to credit return of the different regions (Europe, North America and others). They noticed that Europe had a systematic positive contribution whereas North America had a systematic negative contribution whatever the currency (EUR and USD). Therefore, this transatlantic divide shows that ESG investing was a source of outperformance when it concerned IG bonds of European issuers, but a source of underperformance when it concerned IG bonds of American issuers.
Figure 3.34: Annualized excess return in bps of ESG optimized portfolios (EUR IG, 2010–2013)

Figure 3.35: Annualized excess return in bps of ESG optimized portfolios (EUR IG, 2014–2016)

Source: Ben Slimane et al. (2019b).

Handbook of Sustainable Finance
Figure 3.36: Annualized excess return in bps of ESG optimized portfolios (USD IG, 2010–2013)

Figure 3.37: Annualized excess return in bps of ESG optimized portfolios (USD IG, 2014–2016)

Source: Ben Slimane et al. (2019b).
Box 3.7: Building an optimized ESG portfolio in the fixed-income universe

The ESG score of the portfolio $w = (w_1, \ldots, w_n)$ is the weighted average of the individual scores: $S(w) = \sum_{i=1}^{n} w_i S_i$. If we consider a benchmark $b = (b_1, \ldots, b_n)$, we deduce that the ESG excess score of portfolio $w$ with respect to benchmark $b$ is equal to:

$$S(w \mid b) = \sum_{i=1}^{n} (w_i - b_i) S_i = S(w) - S(b)$$

When we use $z$-scores, we observe that $S(b) \approx 0$ because there is no reason that a capitalization-weighted index has a positive or a negative ESG score. It is generally a neutral ESG portfolio. On the contrary, an ESG portfolio $w$ aims to have a better ESG score than the benchmark: $S(w \mid b) > 0$. When building an optimized ESG portfolio, there is of course a trade-off between the ESG excess score $S(w \mid b)$ and the active or tracking risk $R(w \mid b)$ with respect to the benchmark. For instance, if the active risk is equal to zero, the ESG excess score will be equal to zero. If we consider a high ESG score (e.g., larger than 1.5), we also have to incur a high active risk. Therefore, the optimization problem becomes:

$$w^*(\gamma) = \arg \min_{w} \frac{1}{2} R(w \mid b) - \gamma S(w \mid b)$$

If $\gamma$ is set to zero, the optimized portfolio $w^*(0)$ is the benchmark portfolio $b$. If $\gamma$ is set to infinity, the optimized portfolio $w^*(\infty)$ corresponds to the bond with the largest $z$-score. The parameter $\gamma$ can then be calibrated in order to target a given excess score $S^*$. The issue is the choice of the tracking risk metric. In the case of bonds, we generally use two measures. First, we can match the modified duration of the sectors. It follows that the modified duration risk of portfolio $w$ with respect to benchmark $b$ is:

$$R_{MD}(w \mid b) = \sum_{j=1}^{n_S} \left( \left( \sum_{i \in \text{Sector}(j)} w_i \text{MD}_i \right) - \left( \sum_{i \in \text{Sector}(j)} b_i \text{MD}_i \right) \right)^2$$

where $n_S$ is the number of sectors and $\text{MD}_i$ is the modified duration of bond $i$. An alternative is to use the DTS risk measure:

$$R_{DTS}(w \mid b) = \sum_{j=1}^{n_S} \left( \left( \sum_{i \in \text{Sector}(j)} w_i \text{DTS}_i \right) - \left( \sum_{i \in \text{Sector}(j)} b_i \text{DTS}_i \right) \right)^2$$

where $\text{DTS}_i$ is the duration-times-spread (DTS) factor of bond $i$. We can also define an hybrid approach, where the risk measure is an average of the MD and DTS active risks:

$$R(w \mid b) = R_{MD}(w \mid b) + R_{DTS}(w \mid b)$$

In fact, we can interpret $R_{MD}(w \mid b)$ as an interest rate risk measure and $R_{DTS}(w \mid b)$ as a credit risk measure, while $R(w \mid b)$ is an integrated interest rate/credit risk measure.
Table 3.18: Performance of ESG bond indexes

| Year | FTSE WGBI | | | | | FTSE EGBI | | | | | Bloomberg Euro Aggregate Corporate | | | | |
|------|-----------|------------|------------|------------|------------|--------|------------|------------|--------|--------|------------|------------|--------|--------|
|      | Return | Alpha | Return | Alpha | Return | Alpha | Return | Alpha | Return | Alpha | Return | Alpha | Return | Alpha |
|      | BM | ESG | ESG | BM | ESG | ESG | BM | ESG | ESG | BM | SRI | S-SRI | ESG-S | SRI | S-SRI | ESG-S |
| 2010 | 4.61 | 4.31 | −30 | 0.61 | 4.14 | 353 | 3.07 | 2.93 | 2.96 | −13 | −10 | 2011 | 6.35 | 7.05 | 69 | 3.41 | 7.31 | 391 | 1.49 | 1.17 | 1.43 | −32 | −5 |
| 2012 | 1.65 | 3.06 | 141 | 10.65 | 7.39 | −326 | 13.59 | 13.99 | 12.96 | 40 | −63 | 2013 | −4.00 | −2.95 | 105 | 2.21 | −1.40 | −362 | 2.37 | 2.49 | 2.36 | 12 | −1 |
| 2014 | −0.48 | −0.22 | 26 | 13.19 | 11.44 | −175 | 8.40 | 8.31 | 8.49 | −8 | 10 | 2015 | −3.57 | −4.85 | −128 | 1.65 | 0.39 | −126 | −0.56 | −0.59 | −0.50 | −0.59 | −3 | 6 | −3 |
| 2016 | 1.60 | 1.02 | −59 | 3.20 | 4.00 | 81 | 4.73 | 4.60 | 4.44 | 4.60 | −13 | −29 | −13 | 2017 | 7.49 | 8.16 | 67 | 0.15 | −0.47 | −62 | 2.41 | 2.47 | 2.48 | 2.47 | 6 | 6 | 6 |
| 2018 | −0.84 | −1.41 | −57 | 0.88 | 1.65 | 78 | −1.25 | −1.12 | −1.11 | −1.12 | 13 | 14 | 13 | 2019 | 5.90 | 5.56 | −34 | 6.72 | 4.45 | −227 | 6.24 | 6.01 | 5.92 | 6.01 | −24 | −32 | −24 |
| 2020 | 10.11 | 10.90 | 79 | 5.03 | 4.11 | −92 | 2.77 | 2.69 | 2.70 | 2.52 | −8 | −7 | −25 | 2021 | −6.97 | −7.15 | −17 | −3.54 | −3.76 | −21 | −0.97 | −0.96 | −0.99 | −0.99 | 1 | −2 | −2 |
| 5Y | −2.54 | −3.03 | −49 | −2.33 | −2.95 | −61 | −1.61 | −1.63 | −1.62 | −1.64 | −2 | −1 | −3 | 7Y | −0.58 | −0.93 | −35 | −1.21 | −1.63 | −42 | −0.16 | −0.19 | −0.20 | −0.19 | −3 | −4 | −3 |
| 10Y | −1.22 | −1.46 | −24 | 0.77 | −0.17 | −94 | 0.88 | 0.86 | 0.86 | −2 | −1 | 2019 | 1.00 | 0.96 | −4 | 2020 | 2.47 | 2.80 | 2.87 | 32 | 40 | 2021 | −1.04 | −1.55 | 9.56 | 2.34 | −51 | 1.060 | 338 | 1.10 | 0.40 | 0.21 | −70 | −89 | 2022 | −15.76 | −15.12 | −1.10 | −13.86 | 64 | 1.467 | 190 | −5.00 | −5.95 | −5.73 | −95 | −72 |

Source: FTSE, Bloomberg & Author’s calculations.
Chapter 3. Impact of ESG Investing on Asset Prices and Portfolio Returns

Bond indexes

In Table 3.18, we compare the annualized returns of some famous bond indexes (FTSE World Government Bond Index or WGBI, FTSE EMU Government Bond Index or EGBI, Bloomberg Euro Aggregate Corporate Total Return Index, Bloomberg US Corporate Total Return Index and Bloomberg Global High Yield Total Return Index) with the annualized returns of their ESG equivalent indexes\textsuperscript{29}. Results with bond indexes are close to those obtained with equity indexes. Indeed, ESG investing has its good and bad times. Nevertheless, we notice that the results are less balanced than previously. It seems that ESG investing creates positive alpha less frequently in the bond market. In fact, the main reason is that ESG bond indexes has lower carry because they have a better credit rating\textsuperscript{30}.

3.2.3 Cost of capital

Equity

Corporate debt

Sovereign debt

3.3 Strategic asset allocation


\textsuperscript{29}For the FTSE WGBI and EGBI, we consider the FTSE ESG World Government Bond and FTSE ESG Select EMU Government Bond indexes. For the Bloomberg Euro Aggregate Corporate TR Index, we use the MSCI Euro Corporate SRI TR Index (SRI), Bloomberg MSCI Euro Corporate Sustainable SRI TR Index (S-SRI), and Bloomberg MSCI Euro Corporate ESG Sustainability SRI (ESG-S). For the Bloomberg Euro Aggregate Corporate TR Index, we use the MSCI Euro Corporate SRI TR Index (SRI), Bloomberg MSCI Euro Corporate Sustainable SRI TR Index (S-SRI), and Bloomberg MSCI Euro Corporate ESG Sustainability SRI (ESG-S). For the Bloomberg US Corporate TR Index, the comparison is done with the Bloomberg MSCI US Corporate SRI Select Index (SRI), Bloomberg MSCI US Corporate Sustainable SRI TR Index (S-SRI) and Bloomberg MSCI US Corporate ESG Sustainability SRI (ESG-S). Finally, the Bloomberg Global High Yield Total Return Index is compared with the Bloomberg MSCI Global High Yield SRI Index (SRI) and Bloomberg MSCI Global High Yield Sustainability Index (SUS).

\textsuperscript{30}The relationship between ESG and credit ratings is investigated in Section 3.2.3 on page 200.
3.4 Exercises

3.4.1 Equity portfolio optimization with ESG scores

We consider the CAPM model:

\[ R_i - r = \beta_i (R_m - r) + \varepsilon_i \]

where \( R_i \) is the return of asset \( i \), \( R_m \) is the return of the market portfolio \( w_m \), \( r \) is the risk free asset, \( \beta_i \) is the beta of asset \( i \) with respect to the market portfolio and \( \varepsilon_i \) is the idiosyncratic risk of asset \( i \). We have \( R_m \perp \varepsilon_i \) and \( \varepsilon_i \perp \varepsilon_j \). We note \( \sigma_m \) the volatility of the market portfolio. Let \( \tilde{\sigma}_i \), \( \mu_i \) and \( S_i \) be the idiosyncratic volatility, the expected return and the ESG score of asset \( i \). We use a universe of 6 assets with the following parameter values:

<table>
<thead>
<tr>
<th>Asset ( i )</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \beta_i )</td>
<td>0.10</td>
<td>0.30</td>
<td>0.50</td>
<td>0.90</td>
<td>1.30</td>
<td>2.00</td>
</tr>
<tr>
<td>( \tilde{\sigma}_i ) (in %)</td>
<td>17.00</td>
<td>17.00</td>
<td>16.00</td>
<td>10.00</td>
<td>11.00</td>
<td>12.00</td>
</tr>
<tr>
<td>( \mu_i ) (in %)</td>
<td>1.50</td>
<td>2.50</td>
<td>3.50</td>
<td>5.50</td>
<td>7.50</td>
<td>11.00</td>
</tr>
<tr>
<td>( S_i )</td>
<td>1.10</td>
<td>1.50</td>
<td>2.50</td>
<td>-1.82</td>
<td>-2.35</td>
<td>-2.91</td>
</tr>
</tbody>
</table>

and \( \sigma_m = 20\% \). The risk-free return \( r \) is set to 1\% and the expected return of the market portfolio \( w_m \) is equal to \( \mu_m = 6\% \).

1. We assume that the CAPM is valid.

   (a) Calculate the vector \( \mu \) of expected returns.

   (b) Compute the covariance matrix \( \Sigma \). Deduce the volatility \( \sigma_i \) of the asset \( i \) and find the correlation matrix \( C = (\rho_{i,j}) \) between asset returns.

   (c) Compute the tangency portfolio \( w^* \). Calculate \( \mu (w^*) \) and \( \sigma (w^*) \). Deduce the Sharpe ratio and the ESG score of the tangency portfolio.

   (d) Compute the beta coefficient \( \beta_i (w^*) \) of the six assets with respect to the tangency portfolio \( w^* \), and the implied expected return \( \tilde{\mu}_i \):

\[
\tilde{\mu}_i = r + \beta_i (w^*) (\mu (w^*) - r)
\]

   (e) Deduce the market portfolio \( w_m \). Comment on these results.

2. We consider long-only portfolios and we also impose a minimum threshold \( S^* \) for the portfolio ESG score:

\[ S (w) = w^\top S \geq S^* \]

   (a) Let \( \gamma \) be the risk tolerance. Write the mean-variance optimization problem.

   (b) Find the QP form of the MVO problem.

   (c) Compare the efficient frontier when (1) there is no ESG constraint \( (S^* = -\infty) \), (2) we impose a positive ESG score \( (S^* = 0) \) and (3) the minimum threshold is set to 0.5 \( (S^* = 0.5) \). Comment on these results.

   (d) For each previous cases, find the tangency portfolio \( w^* \) and the corresponding risk tolerance \( \gamma^* \). Compute then \( \mu (w^*) \), \( \sigma (w^*) \), \( SR (w^* | r) \) and \( S (w^*) \). Comment on these results.
(e) Draw the relationship between the minimum ESG score $S^*$ and the Sharpe ratio $SR (w^* | r)$ of the tangency portfolio.

(f) We assume that the market portfolio $w_m$ corresponds to the tangency portfolio when $S^* = 0.5$.

i. Compute the beta coefficient $\beta_i (w_m)$ and the implied expected return $\tilde{\mu}_i (w_m)$ for each asset. Deduce then the alpha return $\alpha_i$ of asset $i$. Comment on these results.

ii. We consider the equally-weighted portfolio $w_{ew}$. Compute its beta coefficient $\beta (w_{ew} | w_m)$, its implied expected return $\tilde{\mu} (w_{ew})$ and its alpha return $\alpha (w_{ew})$. Comment on these results.

3. The objective of the investor is twice. He would like to manage the tracking error risk of his portfolio with respect to the benchmark $b = (15\%, 20\%, 19\%, 14\%, 15\%, 17\%)$ and have a better ESG score than the benchmark. Nevertheless, this investor faces a long-only constraint because he cannot leverage his portfolio and he cannot also be short on the assets.

(a) What is the ESG score of the benchmark?

(b) We assume that the investor’s portfolio is $w = (10\%, 10\%, 30\%, 20\%, 20\%, 10\%)$. Compute the excess score $S (w | b)$, the expected excess return $\mu (w | b)$, the tracking error volatility $\sigma (w | b)$ and the information ratio IR $(w | b)$. Comment on these results.

(c) Same question with the portfolio $w = (10\%, 15\%, 30\%, 10\%, 15\%, 20\%)$.

(d) In the sequel, we assume that the investor has no return target. In fact, the objective of the investor is to improve the ESG score of the benchmark and control the tracking error volatility. We note $\gamma$ the risk tolerance. Give the corresponding esg-variance optimization problem.

(e) Find the matrix form of the corresponding QP problem.

(f) Draw the esg-variance efficient frontier $(\sigma (w^* | b), S (w^* | b))$ where $w^*$ is an optimal portfolio.

(g) Find the optimal portfolio $w^*$ when we target a given tracking error volatility $\sigma^*$. The values of $\sigma^*$ are 0%, 1%, 2%, 3% and 4%.

(h) Find the optimal portfolio $w^*$ when we target a given excess score $S^*$. The values of $S^*$ are 0, 0.1, 0.2, 0.3 and 0.4.

(i) We would like to compare the efficient frontier obtained in Question 3(f) with the efficient frontier when we implement a best-in-class selection or a worst-in-class exclusion. The selection strategy consists in investing only in the best three ESG assets, while the exclusion strategy implies no exposure on the worst ESG asset. Draw the three efficient frontiers. Comment on these results.

(j) Which minimum tracking error volatility must the investor accept to implement the best-in-class selection strategy? Give the corresponding optimal portfolio.

3.4.2 Bond portfolio optimization with ESG scores

3.4.3 Minimum variance portfolio with climate risk

3.4.4 Cost of capital and green sentiment

3.4.5 Strategic asset allocation with ESG preferences
Chapter 4

Sustainable Financial Products

4.1 The market of ESG mutual funds
4.1.1 Greenwashing issues
4.1.2 Classification of ESG investment funds
4.1.3 The case of index funds
4.1.4 Market growth statistics
4.2 Green and social bonds

Beside traditional investment vehicles that incorporate ESG criteria, we can find a category of securities that is entirely dedicated to sustainable finance. It corresponds to specific sustainable debt instruments. The two most famous assets are green bonds and social bonds, but the list of sustainable fixed-income assets is much longer: sustainable bonds, transition bonds, sustainable-linked bonds, green loans, green notes, green ABCP notes, etc. In Table 4.1, we report the segmentation of the sustainable fixed-income market. According to CBI (2022b), the cumulative total GSS+ issuance stands at $3.3 tn at the end of June 2022. About $3 tn comes from GSS assets (Figure 4.1). We have the following breakdown: 62.3% for green bonds, 17% for social bonds and 20.7% for sustainability bonds. The market is dominated by DM issuers (approximately 63%), while the remaining part is half of EM issuers and half of supranational issuers.

<table>
<thead>
<tr>
<th>Theme</th>
<th>Label</th>
<th>Format</th>
</tr>
</thead>
<tbody>
<tr>
<td>GSS</td>
<td>Green</td>
<td>Use of proceeds</td>
</tr>
<tr>
<td></td>
<td>Social</td>
<td>Use of proceeds</td>
</tr>
<tr>
<td></td>
<td>Sustainability</td>
<td>Use of proceeds</td>
</tr>
<tr>
<td>Transition</td>
<td>Sustainability-Linked</td>
<td>Entity KPI-linked</td>
</tr>
<tr>
<td></td>
<td>Transition</td>
<td>Use of proceeds</td>
</tr>
</tbody>
</table>

Source: CBI (2022b).

Figure 4.1: Issuance of GSS securities (in $ bn)

Source: https://www.climatebonds.net/market/data.
4.2.1 Green bonds

Definition

Green bonds are fixed-income securities, which finance investments with an environmental objective. They differentiate from regular bonds, because they are labelled green by issuers or external third-party entities and there is a commitment to use the funds for financing green projects. However, there is no legally-binding definition of a green bond. Most of market participants\(^1\) have then adopted the definition of the GBP framework\(^2\):

“Green bonds are any type of bond instrument where the proceeds or an equivalent amount will be exclusively applied to finance or re-finance, in part or in full, new and/or existing eligible green projects and which are aligned with the four core components of the Green Bond Principles (GBP).” (ICMA, 2021a, page 3).

The four core components of the GBP are:

1. Use of proceeds
2. Process for project evaluation and selection
3. Management of proceeds
4. Reporting

The utilisation of the proceeds (or the funds) should be affected to eligible green projects, e.g., renewable energy, energy efficiency, pollution prevention (GHG control, soil remediation, waste recycling), sustainable management of living natural resources (sustainable agriculture, sustainable forestry, restoration of natural landscapes), terrestrial and aquatic biodiversity conservation (protection of coastal, marine and watershed environments), clean transportation, sustainable water management, climate change adaptation, circular economy and eco-efficient products, green buildings. With respect to the process for project evaluation and selection, the issuer of a green bond should clearly communicate the environmental sustainability objectives, the eligible projects and the related eligibility criteria. The third component deals with the management of proceeds and includes the tracking of the “balance sheet” and the allocation of funds\(^3\). It also recommends an external review by a third-party entity. Finally, the reporting must be based on the following pillars: transparency, description of the projects, allocated amounts and expected impacts, qualitative performance indicators and quantitative performance measures\(^4\).

Remark 40 GBP is not the only green bond framework. The other popular guidelines are:

- China Green Bond Principles\(^5\) (PBOC, CBIRC, July 2022)
- Climate Bonds Standard\(^6\) (CBI, 2019)

\(^1\) According to IFC (2020, page 5), the Green Bond Principles are endorsed by 95% of issuers.
\(^2\) The first version of Green Bond Principles was issued on January 2014.
\(^3\) The proceeds should be credited to a sub-account.
\(^4\) Here are some examples: energy capacity, electricity generation, GHG emissions reduced/avoided, number of people provided with access to clean power, decrease in water use, reduction in the number of cars required, etc.
\(^5\) They replace China’s Green Bond Standards published by PBOC in 2015.
\(^6\) The first version is released in November 2011. A new version has been drafted for public consultation and will certainly be available in 2023 (CBI, 2022c).
• ASEAN Green Bond Standards\textsuperscript{7} (ACMF, 2018)

• EU Green Bond Standard\textsuperscript{8}

All these guidelines are based on a common framework and are close to the GBP. The CBI approach, which also uses the GBP, is perhaps more comprehensive and gives more details for issuing a green bond\textsuperscript{9}.

Green debt instruments can be issued in different formats. They differ in the collateral assets, the recourse process in case of default, etc. For instance, the most common instrument is the green regular or “Use of Proceeds” bond (UoP bond), which carries the same credit rating than a conventional bond, because the bondholders have recourse to all the assets of the bond issuer. In the case of a green revenue bond, the collateral for the debt comes from cash flows of the revenue streams collected by the issuer. A green project bond is a bond dedicated to a given green project, implying that the recourse process only concerns the assets related to the project. Green loans are loans that finance green projects and may be secured or unsecured. These four instruments (regular bond, revenue bond, project bond and green loan) are called asset-linked bond structures, because they are related to a specific asset/project. Asset-backed bond structures are made up of securitization and covered bonds. They both involves a group of projects. Securitized bonds can use ABS/MBS/CLO/CDO securitization structures, while covered bonds are German debt instruments (Pfandbriefe) that use a dual recourse process based on the issuer and the cover pool\textsuperscript{10}.

The certification process (or external review) is an important step when issuing green bonds since it is related to the greenwashing issue. We recall that GBP are voluntary process guidelines. They recommend that issuers appoint an external review provider to obtain pre-issuance assessment of the green project and an external auditor to have a post-issuance validation of funding management. Certainly, the most popular form of external review is the second party opinion or SPO (IFC, 2020, page 19). In this case, the objective of the issuer is to obtain a “green bond label” or the approval of its green project by a competent and independent entity, which is recognized by financial markets and investors. For instance, Ehlers and Packer (2017) and IFC (2020) listed the following forms of green bond certification\textsuperscript{11}:

• Second party opinion provided by ESG rating agencies (ISS, Sustainalytics, Vigeo-Eiris);

• Certification by specialized green bond entities (CBI, CICERO, DNV);

• Green bond assessment by statistical rating organizations (Moody’s, S&P).

Some examples

The market of climate-related bonds begins in 2001 with the issuance of a revenue bond (known as the solar bond) by the City of San Francisco. The objective was to finance 140 acres with

\textsuperscript{7}The first version is published in 2017.

\textsuperscript{8}The proposal for a regulation on European green bonds has been released in 2021. It is based on four key requirements: (1) taxonomy-alignment; (2) transparency on how the bond proceeds are allocated through detailed reporting requirements; (3) all European green bonds must be checked by an external reviewer; (4) external reviewers must be supervised by the ESMA.

\textsuperscript{9}See also the Green Bond Handbook published by IFC (2020).

\textsuperscript{10}Investors may have recourse to the issuer, but if the issuer is unable to pay its debt, then bondholders gain recourse to the cover pool.

\textsuperscript{11}Ehlers and Packer (2017) added green bond indexes as a fourth form of certification, since including a bond in a green bond index is a market recognition that the bond is green.
solar panels, which could power renewable energy on homes and business buildings. A second step was reached in 2007, when the European Investment Bank (EIB) issued the world’s first Climate Awareness Bond (CAB) in order to finance renewable energy and energy efficiency projects. Finally, the first green bond has been created by the World Bank and the Swedish bank SEB in 2008 for a group of Scandinavian institutional investors. Since this date, the market of green bonds has been growing at a fast pace. The issued amount has soared from less than $3 bn in 2013 to more than $500 bn in 2021. According to Baker et al. (2022), the years 2013 and 2014 marked the development of the green bond market. For instance, the first corporate green bonds were issued by the French utility company EDF ($1.8 bn) and the Swedish real estate company Vasakronan ($120 bn). Toyota introduced the auto industry’s first-ever asset-backed green bond in 2014 ($1.75 bn), while the Commonwealth of Massachusetts completed the first municipal green bond in 2013 ($100 mn). The development of sovereign green bonds began with Poland in December 2016 ($1 bn) and France in January 2017 ($10 bn).

According to CBI (2022a), the largest corporate issuers in 2021 were China Three Gorges ($7.2 bn), Iberdrola ($3.3 bn), CTP ($3 bn), Ardagh ($2.8 bn), Engie ($2.6 bn), Ford Motor ($2.5 bn), EDP ($2.4 bn), State Grid Corporation of China ($2.4 bn), Mondelez International ($2.4 bn) and Liberty Global ($2.3 bn). Since 2014, the top three corporate issuers are Engie (France), Iberdrola (Spain) and TenneT (Netherlands) with about $17 bn of cumulative issuance for each company. If we focus on sovereign green bonds, the five largest issuers are France ($43.6 bn), Germany ($25.1 bn), UK ($21.9 bn), Italy ($10.0 bn) and Netherlands ($10 bn). The NextGenerationEU program of the European Commission plans to issue $250 bn of green bonds from 2020 to 2030. This will make the European Commission the largest green bonds issuer in the world.

Remark 41 The post-issuance management of a green bond may be an issue. For example, Mexico City Airport Trust issued $6 bn of green bonds in 2016 and 2017 in order to finance the construction of a new airport. It met ICMA GBP and obtained a second party opinion from Sustainalytics as well as green bond assessments from rating agencies Moody’s and S&P. However, in October 2018, the new Mexican government announced to halt the construction of the airport and launched a buyback package, capped at $1.8 bn.

The green bond market

Statistics From 2007 to the first half of 2022, CBI estimate that a total of 10 800 green bonds have been issued in the world. The geographic repartition is the following: 52% in North America, 23% in Europe, 17% in Asia-Pacific and 8% in the rest of the world (including supranational entities). The distribution of deal size is highly skewed. Indeed, 70% of green bonds have a notional less than $100 mn, whereas 3.2% of them have a deal size greater than $1 bn. If we focus on the number of issuers, we obtain the following top five ranking: 500 in US, 404 in China, 156 in Japan, 104 in Sweden and 63 in Norway. If we analyze the amount issued, the size of the green bond market is roughly equal to $1.9 tn. In Figures 4.2 and 4.3, we have reported the issuance and notional outstanding (or cumulative issuance) by market type and region from 2014 to 2022. The market is lead by Europe (46%), followed by Asia-Pacific (25%) and North America (20%). The issuance of green bonds
Chapter 4. Sustainable Financial Products

Figure 4.2: Issuance and notional outstanding of green debt by market type

Figures 4.3: Issuance and notional outstanding of green debt by region

Source: https://www.climatebonds.net/market/data

Handbook of Sustainable Finance
Chapter 4. Sustainable Financial Products

Figure 4.4: Issuance and notional outstanding of green debt by use of proceeds

Figure 4.5: Issuance and notional outstanding of green debt by issuer type

Source: https://www.climatebonds.net/market/data.
mainly concerns four sectors: energy, buildings, transport and water. They represent 88% of the market (Figure 4.4). An analysis by issuer type shows the market is approximately balanced between financials (development banks and financial corporates), government/sovereign issuers (including government-backed entities, local governments and states) and non-financial corporations (Figure 4.5).

**How to invest in green bonds**  There are several ways to invest in green bonds. We can consider a mutual fund (active management), an ETF (passive management) or a direct investment

17 Only largest institutional investors have access to the primary green bond market. Nevertheless, they can trade green bonds in the secondary market.

- Bloomberg Barclays MSCI Global Green Bond Index (global green bonds)
- S&P Green Bond Index (global green bonds)
- Solactive Green Bond Index (global green bonds)
- ChinaBond China Climate-Aligned Bond Index (chinese green bonds)
- SSE Green Corporate Bond Index and SSE Green Bond Index (green bonds listed on the Shanghai Stock Exchange)
- ICE BofA Green Index (global green bonds)

**The economics of green bonds**

**Rationale for issuing green bonds**  Green bonds are very different from ESG portfolios and funds, since the objective is to finance a specific green project. Therefore, the choice to invest in a green bond goes beyond CSR or SRI values (Maltais and Nykvist, 2020). From the issuer viewpoint, it is a signal and a visible endorsement that the entity participates to the green economy (Flammer, 2021; Daubanes et al., 2021). From the investor viewpoint, it is a way to implement relatively easily an impact investing program. Furthermore, green bonds are more climate-related assets than ESG-related assets. They strongly participate to financing the climate transition. For instance, sovereign green bond issuance is generally presented as a response to climate change. If we consider the NextGenerationEU program of green bonds, the objective of the European Commission is to “achieve the goal of climate neutrality by 2050”. Denmark issued its first green bond on January 2022 and the funds will be allocated to “support the production of renewable energy sources and the green transition of the transport sector”. The success of the Republic of the Philippines is explained as the strong recognition and confidence from investors to “achieving sustainable development and mitigating climate change, notably the pledge to reduce our greenhouse gas emissions by 75% by 2030”. Therefore, a green bond is a signaling tool to show that governments and corporations
respond to climate change. This is the main conclusion of the research conducted by Caroline Flammer:

"I show that investors respond positively to the issuance announcement, a response that is stronger for first-time issuers and bonds certified by third parties. The issuers improve their environmental performance post-issuance (i.e., higher environmental ratings and lower CO₂ emissions) and experience an increase in ownership by long-term and green investors. Overall, the findings are consistent with a signaling argument — by issuing green bonds, companies credibly signal their commitment toward the environment." (Flammer, 2021, page 499)

From an economic viewpoint, green bonds can be seen as a second-best instrument in the absence of a global carbon pricing scheme (carbon tax), which is the Pigovian solution to the carbon externality (Ehlers and Packer, 2017; Daubanes et al., 2021; Baker et al., 2022). In this perspective, green bonds are the response to the net zero financing issue:

"Capital spending on physical assets for energy and land-use systems in the net-zero transition between 2021 and 2050 would amount to about $275 trillion, or $9.2 trillion per year on average, an annual increase of as much as $3.5 trillion from today" (McKinsey, 2022, page viii).

This figure of $3.5 trillion is approximately equal to 1/2 of global corporate profits, 1/4 of total tax revenue, or 4.1% of world GDP. Therefore, the gap between current and expected green investments is huge. Of course, green bonds help to finance the climate transition, but they are a partial solution since they represented less than $600 mn of investment in 2021. Therefore, the second-best instrument is not currently the solution to climate change.

The last remark questions us whether the green bond market is driven by the supply or the demand. Indeed, if green bonds are a second-best solution, we should observe a greater supply. The issue is that there is apparently no economic incentive with the exception of green signaling. In this case, the temptation is to conclude that the green bond market is driven by the demand of green assets. It is true that we observe a systematic oversubscription when issuing a green bond. We have already seen that the issuance of the EC in October 2021 has been oversubscribed 11 times. Such events are not rare. For example, the Italian green BTP was 9 times oversubscribed in December 2020, the German green bond was more than 5 times oversubscribed in September 2020, etc. Because of this supply/demand imbalance, we could think that green and conventional bond prices are different for the same issuer even if the green and conventional bonds share the same characteristics (same coupon, same maturity, same seniority, same payment schedule). In particular, we expect a large negative premium of the green bond with respect to the conventional bond. Below, we are going to see that the difference is relatively low, which is a market anomaly. In Section 8.3 on page 317, we will learn that a global and fair carbon tax implies a strong distortion of the economic profitability across companies and sectors. On the contrary, green bond policies have little impact, meaning that green bonds are not really a second-best instrument. They help to capture investment flows and finance the climate transition because of the huge demand from investors, but the cost of greening the economy remains relatively high, because they have low impact on negative carbon externalities, adverse selection and moral hazard. In this context, the development of green bonds is disappointing if the goal is to fight the climate change and reduce dramatically carbon emissions. Nevertheless, the development of green bonds is also positive because it participates to the emergence and the diffusion of the green sentiment (Brière and Ramelli, 2021).

\[^{18}For instance, we observe a high issuance activity just before and during the organization of a Conference of Parties (COP) to the UNFCCC.\]
Estimation of the greenium  The green bond premium (or greenium) is the difference in pricing between green and regular bonds. Financial theory tells us that the yield of a bond depends on its characteristics (maturity, cash flow schedule, coupon rate, seniority, liquidity), the term structure of the interest rates and the default risk of the bond issuer (Roncalli, 2020a, pages 131-136). Therefore, if we compare the yield of a green bond with the yield of a regular bond issued by the same issuer, the difference must be equal to zero if the two bonds have the same characteristics or if they are twin bonds (Box 4.1). In practice, this is generally not the case. From a mathematical viewpoint, the greenium is defined as:
\[
g = y(\text{GB}) - y(\text{CB})
\]
where \( y(\text{GB}) \) is the yield (or return) of the green bond and \( y(\text{CB}) \) is the yield (or return) of the conventional twin bond\(^{19}\). Let \( s = y - y^* \) be the difference between the yield with default risk and the yield without default risk. Another expression of the greenium is:
\[
g = \underbrace{s(\text{GB}) - s(\text{CB}) + y^*(\text{CB}) - y^*(\text{GB})}_{\approx 0}
\]
Therefore, we can also define the greenium as the spread difference between the green bond and the conventional bond.

\[\text{Box 4.1: Green twin bonds}\]

The twin bond concept has been introduced in 2020 by Germany. The underlying idea is that investors in German green bonds may swap their holdings with a conventional German government bond with the same maturity and coupon at any time, but not vice-versa. The objective is to increase the marketability of green bonds and improve the liquidity of the green bond market. The ability to compare two bonds from the same issuer with an equivalent maturity and coupon provides a direct measure of the greenium.

On 3 September 2020, the 10-year German green bond with a coupon of 0.00% was priced 1 basis point below the 10-year conventional German bond. On 19 January 2022, Denmark issued a 10-year green bond with the same maturity, interest payment dates and coupon rate as the conventional 2031 Danish bond. The effective yield of the green bond was 5 basis points below the twin regular bond.

Remark 42  The concept of bond yield (or bond return) is relatively complex, because there is not a unique approach to compute the financial return of a bond. Generally, we use the yield to maturity, but we can also use the credit spread if we prefer to measure the excess return. Another popular measure is the current yield, which is equal to the next coupon value divided by the current market price of the bond.

Example 17  We consider a 10-year green bond GB\(_1\) whose current price is equal to 91.35. The corresponding conventional twin bond is a 20-year regular bond, whose remaining maturity is exactly equal to ten years and its price is equal to 90.07. We assume that the two bonds have the same coupon level\(^{20}\), which is equal to 4%.

\(^{19}\)This means that the conventional bond has the same characteristics than the green bond.

\(^{20}\)This assumption is not realistic since the regular bond has been issued 10 years before the green bond. In this case, we expect that the coupon of the regular bond was higher than the coupon of the green bond.
Box 4.2: Bond pricing

We consider that the bond pays coupons \( C(t_m) \) with fixing dates \( t_m \) and the notional \( N \) (or the par value) at the maturity date \( T \). The cash flow scheme is reported in Figure 4.A. Knowing the yield curve, the price of the bond without default risk at the date \( t \) satisfies the following relationship (Roncalli, 2020a, Equation 3.2):

\[
P_t + AC_t = \sum_{t_m \geq t} C(t_m) B_t(t_m) + N B_t(T)
\]

where \( B_t(t_m) \) is the discount factor at time \( t \) for the maturity date \( t_m \) and \( AC_t \) is the accrued coupon. \( P_t + AC_t \) is called the dirty price whereas \( P_t \) refers to the clean price. The yield to maturity of the bond is the discount rate which returns its market price:

\[
\sum_{t_m \geq t} C(t_m) e^{-(t_m-t)y} + N e^{-(T-t)y} = P_t + AC_t
\]

Figure 4.A: Cash flows of a bond without default risk

By introducing the credit risk of the issuer, the cash flows may be different because the issuer may default at time \( \tau < T \) (Figure 4.B). Roncalli (2020a, Equation 3.3) shows that:

\[
P_t + AC_t = \sum_{t_m \geq t} C(t_m) B_t(t_m) S_t(t_m) + N B_t(T) S_t(T) + R N \int_t^T B_t(u) f_t(u) \, du
\]

where \( R \) is the recovery rate, \( S_t(u) \) is the survival function at time \( u \) and \( f_t(u) \) the associated density function. The yield to maturity of the defaultable bond is computed exactly in the same way as without default risk. The credit spread \( s = y - y^* \) is then defined as the difference of the yield to maturity \( y \) with default risk and the yield to maturity \( y^* \) without default risk.

Figure 4.B: Cash flows of a bond with default risk
Let us consider Example 17. The computation of the yield to maturity\(^ {21} \) gives \( y(\text{GB}) = 5\% \) and \( y(\text{CB}) = 5.169\% \). We deduce that the greenium is equal to \(-16.9\) bps. If we assess the bond return with the current yield, we have \( y(\text{GB}) = 4/91.35 = 4.379\% \) and \( y(\text{CB}) = 4/90.07 = 4.441\% \). In this case, we obtain \( g = -6.2 \) bps. We notice that the two measures are different even if the greenium is negative in both cases.

![Figure 4.6: Greenium in bps of the German green bond (DBR 0% 15/08/2030)](image)

Source: ICE (2022).

In the case of twin bonds, we can easily compute the greenium since the green and regular bonds have exactly the same characteristics and are issued at the same date. In Figure 4.6, we report the dynamics of the greenium for the German Bund 0% 15/08/2030. This analysis comes from the research study of Pástor et al. (2022). We observe that the greenium is always negative since the inception date (08/09/2020). On average, the greenium is equal to \(-3.27\) bps. Its range is between \(-7\) and \(+1\) bps. Another illustration of the greenium is provided by Zerbib (2019), who analyzed the perpetual 5.5 year callable green hybrid bond that was issued by Iberdrola on 14 November 2017:

“At the beginning of the day, the coupon price was estimated at 2.2\%–2.375\%. The issue was quickly oversubscribed to 3.3 billion euros [compared to the initial offering of 1 billion euros], and the final coupon was eventually priced at 1.875\%, i.e., 5 bps below the conventional benchmark”. (Zerbib, 2019).

In both cases (German and Iberdrola bonds), we must distinguish the greenium observed in the primary market (when bonds are originated) and the greenium priced in the secondary market (when bonds are traded). In the primary market, a negative greenium implies that the investor has bought

\(^{21}\text{We solve the equation } \sum_{t=1}^{10} 4e^{-t\gamma} + 100e^{-10\gamma} = P \text{ where } P = 91.35 \text{ for the green bond and } P = 90.07 \text{ for the conventional bond.}\)
a green bond with a lower coupon rate compared to the coupon rate offered by the conventional bond. In the secondary market, a negative greenium implies that the investor has bought a green bond with a higher price compared to the market price of the conventional bond. Let $c$ be the coupon rate. Mathematically, we have $c(GB) \leq c(CB)$ in the first case and $P_t(GB) \geq P_t(CB)$ in the second case.

The estimation of the greenium is a difficult task. First, we have to distinguish primary and secondary markets. Most of academic studies concern the secondary market, because there are few observations to compute the greenium in the primary market. Indeed, we can only have one observation per green bond in this last case (the day when the green bond is issued). Nevertheless, the different academic studies generally estimate a negative greenium between 5 and 15 bps on the primary market (Ehlers and Packer, 2017; Gianfrate and Peri, 2019; Fatica et al., 2021; Kapraun et al., 2021; Löffler et al., 2021; Baker et al., 2022). These results confirm the professional consensus that the greenium is negative and significant at the issuance date. However, the persistence of the negative greenium in the secondary market is an issue and an open debate. We observe two opposing sides: those who consider that the negative greenium persists and remains statistically significant, and those who think that the negative greenium vanishes. For instance, Zerbib (2019) found a greenium of $−2$ bps for EUR and USD global bonds from July 2013 to December 2017. While they measured a greenium of $−18$ bps in the primary market, the estimates of Gianfrate and Peri (2019) are respectively $−11$, $−13$ and $−5$ bps for three trading dates\textsuperscript{22}. Generally, when academics estimate the greenium both in the primary and secondary markets, they observe that the discount premium is higher at the issuance date. However, some academic studies consider that the greenium in the secondary market is zero and statistically insignificant for municipal bonds (Larcker et al., 2020) and corporate bonds (Tang and Zhang, 2020; Flammer, 2021).

The second issue when estimating the greenium is the choice of the bond yield return. In Figure 4.7, we report the value of the greenium computed with different spread measures in the case of the German green bond. All these measures give different results. If we consider the spread to worst, the average greenium is $−2.73$ bps versus $−3.27$ bps for the effective yield.

The last issue is the estimation method. According to Ben Slimane et al. (2020), there are two main approaches:

1. The bottom-up matching approach consists in computing the yield difference at the bond level. This means that we compare the green bond of an issuer with a synthetic conventional bond of the same issuer that has the same characteristics in terms of currency, seniority and duration (Zerbib, 2019). This matching methodology may be relaxed by considering a conventional bond of another issuer in the same country and industry and with the same rating (Flammer, 2021).

2. The top-down replication approach consists in computing the yield difference at the portfolio level. The underlying idea is to consider a diversified portfolio of green bonds and replicate it with a portfolio of conventional bonds. The objective of the replication process is to avoid biases in terms of currency, sector, credit rating, maturity, etc. Therefore, the greenium is the difference between the yield of the green bond portfolio and the yield of the replication portfolio.

In the bottom-up approach, we first filter all the conventional bonds, which has the same issuer, the same currency, and the same seniority of the green bond GB. Then, we select the two conventional

\textsuperscript{22}They are 10 January, 7 July and 14 December 2017
bonds CB₁ and CB₂ which are the nearest in terms of modified duration:

$$|MD\ (GB) - MD\ (CB_j)|_{j \neq 1,2} \geq \sup_{j=1,2} |MD\ (GB) - MD\ (CB_j)|$$

Finally, we perform the linear interpolation/extrapolation of the two yields $y(CB₁)$ and $y(CB₂)$ such that the modified duration of the synthetic conventional bond is exactly equal to the modified duration of the green bond. For instance, by assuming that $MD\ (CB₁) \leq MD\ (CB₂)$, the synthetic yield is:

$$y(CB) = y(CB₁) + \frac{MD\ (GB) - MD\ (CB₁)}{MD\ (CB₂) - MD\ (CB₁)} (y(CB₂) - y(CB₁))$$

**Example 18** We consider a green bond, whose modified duration is 8 years. Its yield return is equal to 132 bps. We can surround the green bond by two conventional bonds with modified duration 7 and 9.5 years. The yield is respectively equal to 125 and 148 bps. The interpolated yield is equal to:

$$y(CB) = 125 + \frac{8 - 7}{9.5 - 7} (148 - 125) = 134.2 \text{ bps}$$

It follows that the greenium is equal to $-2.2$ bps:

$$g = 132 - 134.2 = -2.2 \text{ bps}$$

In the second approach proposed by Fender *et al.* (2019), we consider a portfolio $w$ of green bonds. We have:

$$w = (w₁, \ldots, wₙ)$$
where \( n \) is the number of green bonds. Then, we perform a clustering analysis by considering the 4-uplets (Currency \( \times \) Sector \( \times \) Credit quality \( \times \) Maturity). Let \((C_h, S_j, R_k, M_l)\) be an observation for the 4-uplet (e.g. EUR, Financials, AAA, 1Y-3Y). We compute its weight:

\[
\omega_{h,j,k,l} = \sum_{i\in(C_h, S_j, R_k, M_l)} w_i
\]

The greenium is then defined as the weighted excess yield:

\[
g = \sum_{h,j,k,l} \omega_{h,j,k,l} \left( y_{h,j,k,l} (\text{GB}) - y_{h,j,k,l} (\text{CB}) \right)
\]

where \( \omega_{h,j,k,l} \) is the weight of the cluster \((C_h, S_j, R_k, M_l)\) in the green portfolio, \( y_{h,j,k,l} (\text{GB}) \) is the yield of the cluster in the green portfolio and \( y_{h,j,k,l} (\text{CB}) \) is the yield of the cluster in the benchmark portfolio.

Figure 4.8 shows the evolution of the greenium (expressed in bps), which has been computed by Ben Slimane et al. (2020) with the top-down approach. On average, it is negative and equal to \(-4\) bps. The 95\% confidence interval corresponds to the range \(-7.9\) to \(-1.3\) bps. Since the covid-19 crisis, we observe that the greenium tends to decrease in absolute value. Nevertheless, we notice that the greenium highly depends on the currency. The greenium of EUR-denominated bond is lower than the greenium of USD-denominated bond on average \((-5.6\text{ vs. } -3.3\text{ bps})\), but this is not the case in 2022 \((-1.9\text{ vs. } -9.3\text{ bps})\). The correlation between EUR and USD premia changes over time and is not very high in absolute value. For instance, it is equal to 29\% since 2020. These differences do not only concern currencies, but also sectors, maturities, regions and ratings. For example, the greenium is not statistically significant for many sectors. Ben Slimane et al. (2020) also found that the volatility of green bond portfolios are lower than the volatility of conventional bond portfolios, implying that green and conventional bonds have identical Sharpe ratio since the last five years. To summarize, we can assume that the greenium is slightly negative, but the order of magnitude is relatively low.

### 4.2.2 Social bonds

**Definition**

In the mid of 2010s, the concept of green bonds has been extended to social objectives. The first social bond is issued in January 2015 by Spanish Instituto de Credito in order to help finance SMEs in economically depressed regions of Spain. In September 2015, Kutxabank issued the first social covered bond and the proceeds of the bond were used for financing and subsiding social housing projects in the Basque region. Since 2015, the framework of social bonds has evolved, but it is now a copy/paste version of the green bond framework. For example, the definition of a social bond is exactly the same as for green bonds:

“Social Bonds are any type of bond instrument where the proceeds, or an equivalent amount, will be exclusively applied to finance or re-finance in part or in full new and/or existing eligible social projects and which are aligned with the four core components of the Social Bond Principles (SBP).” (ICMA, 2021b, page 3).

Again, the four core components are principles are based the use of proceeds, the process for project evaluation and selection, the management of proceeds and the reporting. The social project cate-
The categories are: affordable basic infrastructure\textsuperscript{23}, access to essential services\textsuperscript{24}, affordable housing, employment generation\textsuperscript{25}, food security and sustainable food systems\textsuperscript{26}, and socioeconomic advancement and empowerment\textsuperscript{27}. The use of proceeds also introduces the concept of target population, meaning that the objective of a social bond is defined by both a social project category and a target population. Examples of target populations are: (1) living below the poverty line, (2) excluded and/or marginalised populations and/or communities, (3) people with disabilities, (4) migrants and/or displaced persons, (5) undereducated, (6) underserved, owing to a lack of quality access to essential goods and services, (7) unemployed, (8) women and/or sexual and gender minorities, (9) aging populations and vulnerable youth and (10) other vulnerable groups, including as a result of natural disasters. The three other components correspond to the ones described in the Green Bond Principles. The only significant difference is that the SBP require that quantitative performance measures include the number of beneficiaries, especially from target populations.

\textsuperscript{23}E.g., clean drinking water, sewers, sanitation, transport, energy.
\textsuperscript{24}E.g., health, education and vocational training, healthcare, financing and financial services.
\textsuperscript{25}Including programs designed to prevent and/or alleviate unemployment stemming from socioeconomic crises, SME financing and microfinance.
\textsuperscript{26}E.g., physical, social, and economic access to safe, nutritious, and sufficient food that meets dietary needs and requirements; resilient agricultural practices; reduction of food loss and waste; and improved productivity of small-scale producers.
\textsuperscript{27}E.g., equitable access to and control over assets, services, resources, and opportunities; equitable participation and integration into the market and society, including reduction of income inequality.
Chapter 4. Sustainable Financial Products

The social bond market

According to CBI, the cumulative issuance of social debt amounts to $515 bn at the end of June 2022. In Figure, we report the dynamics of the debt issuance. We notice a high growth in 2020, which is due to the issuance of social bonds to finance the covid debt. According to CBI, the market is dominated by European issuers (46%) and supranational issuers (29%). Most of social bonds are issued by the public sector (72%) followed by financials (15.7%), development banks (7.7%) and corporations (4.6%).

Figure 4.9: Issuance of social bonds

Source: https://www.climatebonds.net/market/data.

4.2.3 Other sustainability-related instruments

Sustainability bonds

Sustainability bonds are debt instruments that are issued to finance projects or activities that have both positive environmental and social impacts. The underlying idea is that some social projects may also have environmental co-benefits, and vice-versa. Sustainability bonds are aligned with the four core components of both the GBP and SBP. An example is the Series 2021 sustainability bonds issued by the American Museum of Natural History. The environmental objective is to partially finance the Gilder Center (green buildings), while the social objectives are to expand access to critical science education, and promote biocultural diversity and research. The social benefits accrue to target populations that include K-12 STEM education shortage areas and the general public.

Remark 43 According to CBI, the cumulative issuance of sustainability bonds reaches $620 bn at the end of June 2022.
Box 4.3: Examples of social project categories and target populations

- **Instituto de Crédito Oficial** (Spanish state-owned bank, March 2020)
  “The Social Bond proceeds under ICO’s Second — Floor facilities will be allocated to loans to finance small, medium and micro enterprises with an emphasis on employment creation or employment retention in: (1) specific economically underperforming regions of Spain; (2) specific municipalities of Spain facing depopulation; (3) regions affected by a natural disaster. [...] The target populations are SMEs in line with European Union’s standards.”

- **Pepper Money** (non-bank lender in Australia and New Zealand, April 2022)
  “The positive social impact of a Pepper Money eligible social project derives from its direct contribution to improving access to financial services and socio-economic empowerment, by using proprietary systems to make flexible loan solutions available to applicants who are not served by traditional banks. [...] Pepper Money is seeking to achieve positive social outcomes for a target population of Australians that lack access to essential financial services and experience inequitable access to and lack of control over assets. Pepper Money directly aims to address the positive social outcome of home ownership for borrowers who may have complexity in their income streams, gaps in their loan documentation or have adverse credit history. Traditionally, this cohort has been underserved by banks that rely on inflexible algorithmic loan application processing.”

- **Danone** (French multinational food-products corporation, March 2018)
  “The eligible project categories are: (1) research & innovation for advanced medical nutrition (target populations: infants, pregnant women, patients and elderly people with specific nutritional needs), (2) social inclusiveness (target populations: farmers, excluded and/or marginalised populations and/or communities, people living under the poverty line, rural communities in developing countries), (3) responsible farming and agriculture (target populations: milk producers, farmers), etc.”

- **Korian** (European care group, October 2021)
  “The proceeds of any instrument issued under the framework will be used [...] to provide services, solutions, and technologies that will enable Korian to meet at least one of its social objectives: (1) to increase and improve long-term care nursing home capacity for dependent older adults; (2) to increase and improve medical capacity for people in need of medical support; (3) to increase and improve access to alternative, nonmedical services, technologies, and housing solutions that facilitate the retention of older adults’ autonomy; and (4) to improve the daily provision of care to and foster a safer living environment for its patients. [...] Furthermore, Korian’s target populations are older adults, which Korian defines as being over 65 years of age, and those who are dependent on others for some degree of care, which is defined by the health authorities or insurance system of the respective country.”

- **JASSO** (Japan Student Services Organization, July 2022)
  “The social project categories concern the financing of the ‘Category 2 Scholarship Loans’ (interest-bearing scholarship loans that have to be repaid) while the target population is made up of students with financial difficulties.”

Source: Collected from the websites of the organizations.
Sustainability-linked bonds

A sustainability-linked bond (SLB) is a sustainability bond (green/social) plus a step-up coupon if the sustainability KPI is not satisfied. Therefore, a SLB belongs to the family of forward-looking performance-based instruments. The financial characteristics of the bond depends on whether the issuer achieves predefined ESG objectives. Those objectives are:

1. measured through predefined Key Performance Indicators (KPI);
2. assessed against predefined Sustainability Performance Targets (SPT).

Let us give some examples. In September 2019, ENEL issued a general purpose SDG linked bond based on the following SDGs: 7 (affordable and clean energy), 13 (climate action), 9 (industry, innovation and infrastructure) and 11 (sustainable cities and communities). The KPI is renewables installed capacity $RIC$ as of December 31, 2021 while the SPT is equal to 55%. If the SDG 7 objective is not achieved $RIC < 55\%$, ENEL must pay a one-time step-up coupon of 25 bps. On April 2022, the independent report produced by KPMG certifies that “the renewables installed capacity percentage as of December 31, 2021 is equal to 57.5%”. Since 2019, Enel has issued other sustainability-linked bonds.

On 18 February 2021, H&M issued a 8.5-year sustainability-linked bond for a notional of €500 mn. The annual coupon rate is 25 bps and the objectives to achieve by 2025 are:

**KPI$_1$** Increase the share of recycled materials used to 30% (SPT$_1$);

**KPI$_2$** Reduce emissions from the Group’s own operations (scope 1+2) by 20% with 2017 as a baseline (SPT$_2$);

**KPI$_3$** Reduce scope 3 emissions from fabric production, garment manufacturing, raw materials and upstream transport by 10% with 2017 as a baseline (SPT$_3$).

The global step-up rate is equal to:

$$r = 40\% \times \mathbb{1}\{KPI_1 < SPT_1\} +$$

$$20\% \times \mathbb{1}\{KPI_2 < SPT_2\} +$$

$$40\% \times \mathbb{1}\{KPI_3 < SPT_3\}$$

If the three objectives will be achieved, the step-up rate is equal to zero and the step-up coupon is not paid. Otherwise, H&M will pay a step-up coupon proportional to the step-up rate, which can takes the value 20\% (KPI$_2$ is not achieved), 40\% (KPI$_1$ or KPI$_3$ is not achieved), 60\% (KPI$_2$ is not achieved, and KPI$_1$ or KPI$_3$ is not achieved) 80\% (KPI$_1$ and KPI$_3$ are not achieved) or 100\% (KPI$_1$, KPI$_2$ and KPI$_3$ are not achieved). The H&M sustainability-linked bond generated great interest, since it was 7.6 times oversubscribed.

According to (Berrada et al., 2022), “the SLB market has grown strongly since its inception. [...] Bloomberg identifies a total of 434 outstanding bonds flagged as ‘sustainability-linked’ as of February 2022. In contrast, in 2018, there was only a single SLB. The amount raised through the single 2018 SLB issue was $0.22$ bn, whereas the total amount raised through all SLBs issued in 2021 was approximately $160$ bn”. These authors also found that the large majority of SLB issues

---

28 As of 30 June 2019, the KPI was equal to 45.9%.


address exclusively E issues (65%) or a combination of E, S and G issues (17%) or E and G issues (3%). The other combinations are marginal (less than 1% for each). They also noticed that the most frequent KPI concerns GHG emissions (40 %), followed by the issuer’s global ESG score (14 %).

**Transition bonds**

They are financial instruments to support the transition of an issuer, which has significant current carbon emissions. These bonds are typically used to fund projects such as renewable energy developments, energy efficiency upgrades, and other projects that are aimed at transitioning to a more low-carbon economy. The final objective of the bond issuer is always to reduce their carbon emissions. For example, transition bonds can be used to switch diesel powered ships to natural gas or to implement carbon capture and storage.

### 4.3 Sustainable real assets

#### 4.3.1 Green infrastructure

#### 4.3.2 Green real estate

#### 4.3.3 ESG private equity and debt funds
Chapter 5

Impact Investing

5.1 Definition

• Barber et al. (2021)
• Caseau and Grolleau (2020)
• Geczy et al. (2021)

5.2 Thematic funds

5.3 Measurement tools

(CDSB, 2021a,b)

5.4 An example with the biodiversity risk
Chapter 6

Engagement & Voting Policy

Following GSIA (2021), corporate engagement & shareholder action is one of the seven categories of ESG strategies. It is defined as “employing shareholder power to influence corporate behaviour, including through direct corporate engagement (i.e., communicating with senior management and/or boards of companies), filing or co-filing shareholder proposals, and proxy voting that is guided by comprehensive ESG guidelines”. Even if this category of ESG strategies can be found under different names — engagement and voting on sustainability matters for Eurosif, active ownership for the PRI — the scope of ESG engagement is well-marked. It refers to the process of interacting with companies to encourage them to adopt sustainable and socially responsible practices. This may involve discussing issues related to the corporate social responsibility and the sustainability impact of the business with company management and board members, and working with them to develop and implement practices that are aligned with the ESG principles of the shareholder. ESG engagement can be conducted by asset owners, asset managers, or organizations that seek to influence corporate behavior (e.g., Climate Action 100+). However, the ultimate goal of ESG engagement is always to align the ESG practices of corporations with the ESG expectations of investors. ESG engagement is often confused with the term ESG stewardship. In fact, ESG engagement is part of ESG stewardship, but this last one is a broader concept and refers to all the actions that asset owners and managers take to encourage companies to adopt sustainable and socially responsible practices. Of course, engagement is the cornerstone of stewardship because shareholder engagement and voting are the most direct ways to influence companies. Nevertheless, companies are also impacted when an investor implements an ESG scoring or publishes its exclusion list. Increasingly, we notice that the term stewardship replaces the term engagement. For instance, the publication of ESG stewardship reports by asset owners and managers has replaced the publication of ESG engagement in the last three years. In February 2021, the PRI published the guide “Stewardship” on active ownership:

“It guides investors on how to implement the PRI’s Principle 2, which sets out signatories’ commitment to stewardship, stating: we will be active owners and incorporate ESG issues into our ownership policies and practices. [...] The PRI defines stewardship as the use of influence by institutional investors to maximise overall long-term value including the value of common economic, social and environmental assets, on which returns and clients’ and beneficiaries’ interests depend.” (PRI, 2021a).

Even if ESG engagement and ESG stewardship are closely related concepts, ESG stewardship is generally interpreted by investors as their ESG policy, also including rating models, strategies, organizations, etc. In this chapter, we focus on active ownership in a first section and defines the various forms of ESG shareholder activism. In a second section, we study the voting policy of ESG investors.
6.1 Active ownership

6.1.1 Definition

From an ESG viewpoint, the terms active ownership, engagement, and shareholder activism are interchangeable. Shareholder activism is certainly most frequently used by academics, while professionals prefer to speak about engagement and active ownership. A shareholder activist is a shareholder who uses his equity stake in a (listed) company in order to influence the board members, and change the way the firm is managed. For instance, Gillan and Starks (2000) define active shareholders as “investors who, dissatisfied with some aspect of a company’s management or operations, try to bring about change within the company without a change in control”. Changes may concern the business model, the strategy or the ESG policy. On the opposite, passive shareholders are investor who hold shares of the company, but they have no intention to have an influence on the company. When we refer to ESG engagement, the issues focus on sustainable and socially responsible practices.

Conflicting interests between shareholders and management are well-documented and are central in the theory of the firm (Williamson, 1970; Jensen and Meckling, 1976). Indeed, shareholders and management may pursue different objectives. In particular, the concept of “managerial entrenchment” refers to the tendency of managers to act in their own self-interest with a short-term time horizon rather than in the interests of shareholders, whose objective is to improve the long-term performance of the company. In this context, managers can seek to maximise their own utility and not the utility of the shareholders, who are the owners of the firm. For example, managers have incentives that firms grow beyond the optimal size, because it increases their power, the resources under their control and also their compensation (Murphy, 1985). In a similar way, the separation of ownership and control, the social responsibility of business, and the definition of a corporate objective function may result in misalignment of preferences between shareholders and the company board (Jensen and Meckling, 1976). In this context, active shareholders can serve as effective monitors of management behavior, especially when agency costs arise (Jensen, 1993) or negative externalities may generate large potential costs.

The debate about the separation between ownership and control is amplified when we introduce the stakeholder theory (Freeman, 2004). In fact, there may be some conflicts between shareholders and stakeholders, because shareholders do not have necessarily ESG preferences. On page 3, we have already mentioned the debate between the classical shareholder theory and the stakeholder theory. For Friedman (1970), “the social responsibility of business is to increase its profits”. Nevertheless, the shareholder vs. stakeholder debate has changed over time, because more and more investors, especially institutional investors, have now sustainability preferences. Moreover, the corporate social responsibility has evolved quite spectacularly since the seminal publication of Bowen (1953) — see for instance Drucker (1954), Jones (1980), Mintzberg (1983), Drucker (1984), Wood (1991), Mitchell et al. (1997), Carroll (1999), Crowther and Aras (2008), Carroll and Shabana (2010), Jha and Cox (2015) and Yuan et al. (2020). It is now well-accepted that corporations have also social responsibilities. It is summarized by Peter Drucker as follows: “leaders in every single institution and in every single sector ... have two responsibilities. They are responsible and accountable for the performance of their institutions, and that requires them and their institutions to be concentrated, focused, limited. They are responsible also, however, for the community as a whole”. For corporations, this implies an unlimited liability clause with respect to their employees, their consumers, and the society as a whole. One of the main objectives is then to minimize the legal issues. This is specially true for the negative externalities on the environment caused by the company. This echoes the liability risks defined Carney (2015):

“[...] the impacts that could arise tomorrow if parties who have suffered loss or damage
Chapter 6. Engagement & Voting Policy

from the effects of climate change seek compensation from those they hold responsible. Such claims could come decades in the future [...].”

The current context is then completely different than the 1970’s, when Milton Friedman wrote his famous article. Today, corporate social responsibility is no longer an option. Nevertheless, this does not mean that there is a full alignment between management, shareholders and stakeholders.

6.1.2 The various forms of active ownership

According to Bekjarovski and Brière (2018), active ownership can take various forms:

1. Engage behind the scenes with management and the board;
2. Propose resolutions (shareholder proposals);
3. Vote (form coalition, express dissent, call back lent shares);
4. Voice displeasure publicly (in the media);
5. Initiate a takeover (acquire a sizable equity share);
6. Exit (sell shares, take an offsetting bet, divestment);

The first two approaches take the form of dialogue between investors and companies, and involving a direct communication with company management and board members to discuss ESG issues. This is particularly true with the first approach. It is also the case of the second approach, because resolutions are discussed before annual general meetings (AGM). The third approach can be viewed as a one of the financial duties of investors. This is certainly the most common way to participate in the life of the company one a year. The last three approaches take the form of an action or a response when investors do not approve the sustainable policy of the company or the outcomes of the annual general meeting. We generally find all these six approaches (except initiate a takeover) in the engagement/sustainable/stewardship reports of asset owners and managers (Figure 6.1).

Remark 44 The first five approaches are complementary, while exit corresponds to a non-return situation. In the last case, engagement process between the investor and the company is stopped since the investor is no longer a shareholder of the company.

Engage behind the scenes

Meeting the management and the board of a company was very rare twenty years ago. In addition to public meetings following financial performance announcements, communication between investors and investees were generally organized as a morning breakfast event, where a selection of equity or credit analysts is invited to discuss with a representative of the firm, who was generally the chief financial officer. This situation has changed over time, especially with the development of extra-financial analysis. Today, private communications between ESG investors and companies have become very common. Engage behind the scenes corresponds to all the meetings or actions made by the active shareholder to better understand the ESG strategy of firms and challenge companies on some sustainable issues:

“Behind the curtain engagement involves private communication between activist shareholders and the firm’s board or management, that tends to precede public measures such as vote, shareholder proposals and voice. In a sense, the existence of other forms
Figure 6.1: Example of engagement/sustainable/stewardship reports

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="2021InvestmentStewardshipReport.png" alt="Image" /></td>
<td><img src="ResponsibleInvestmentGovernmentPensionFundGlobal2021.png" alt="Image" /></td>
<td><img src="STEWARDSHIPREPORT.png" alt="Image" /></td>
</tr>
<tr>
<td><img src="STEWARDSHIPREPORT2021.png" alt="Image" /></td>
<td><img src="2021SustainableInvestingReport.png" alt="Image" /></td>
<td><img src="USSStewardshipReport2022.png" alt="Image" /></td>
</tr>
<tr>
<td><img src="RaipenStewardshipReport2021.png" alt="Image" /></td>
<td><img src="2021ESGInvestmentStewardshipReport.png" alt="Image" /></td>
<td><img src="StewardshipReport2021.png" alt="Image" /></td>
</tr>
</tbody>
</table>

Source: Corporate websites.

of public activism can be taken as a signal that behind the scene engagements were unsuccessful. When it comes to environmental and social issues, writing to the board or management is a common method though which shareholders can express concern and attempt to influence corporate policy behind the curtain; alternatively, face to face meetings with management or non-executive directors are a more common behind the scene engagement method when it comes to governance.” (Bekjarovski and Brière, 2018, page 10)

In fact, we can classify these face-to-face meetings and more formal exchanges (letters and position statements) into three families:

1. on-going engagement, where the goal for investors is to explain their ESG policy and collect information from the company. For instance, they can encourage companies to adopt best ESG practices, alert companies on ESG risks or better understand sectorial ESG challenges;
2. engagement for influence (or protest), where the goal is to express dissatisfaction with respect to some ESG issues, make recommendations to the firm and measure/control ESG progress of companies;

3. pre-AGM engagement, where the goal is to discuss with companies any resolution items that the investor may vote against.

For many years, engage behind the scenes was very informal and mainly depends on ESG analysts. This is no longer true. Most of investors have now established an engagement process, which is generally based on three steps. First, a list of engagement issues is produced with a few items. The underlying idea is to focus on very important topics, and not to cover anything and everything. Second, a screening is performed for each engagement item in order to identify the most serious cases. Finally, the engagement can begin with the targeted companies. As noticed by the PRI (2019b), policies and processes are important to be formalized, but the ultimate goal of active ownership is obtaining outcomes. Therefore, investors must track their engagements. The different stages are:

- Issues are raised to the company;
- Issues are acknowledged by the company;
- The company develops a strategy to address the issues;
- The company implements changes and the issues are resolved;
- The company did not solve the issues and the engagement failed.

**Remark 45** Even if investors claim that transparency is the pillar of stewardship and engagement practices, they never publish the list of targeted companies and the corresponding issues. Sometimes, they give anonymous examples in their engagement reports.

It is very difficult to obtain public statistics about the engagement behind the scenes and its trend. For instance, Mc Cahery et al. (2016) noticed that “63% of the respondents state that, in the past five years, they have engaged in direct discussions with management, and 45% have had private discussions with a company’s board outside of management’s presence”, but these results are based on a survey of 143 respondents relative to 3 300 invitations that were sent between December 2012 and July 2013. More recently, the study of Barko et al. (2022) is based on a proprietary database, which has been provided by a large European asset manager. We can always find figures from stewardship and engagement reports, but it gives a partial view of this topic. For example, Amundi (French asset manager, €2 064 tn in assets under management) reports 2 334 engagements in 2021 with the following breakdown by ESG themes\(^1\): dialogue to foster a stronger voting exercise and a sounder corporate governance (1 033), transition towards a low carbon economy (547), strong governance for sustainable development (287), social cohesion through the protection of direct and indirect employees (222), natural capital preservation (165) and product, client, societal responsibility (80). The first category corresponds to the 2021 pre-AGM dialogue statistics, meaning that the Amundi corporate governance team conducted dialogue with 1 033 issuers in 2021. The 2 334 engagements can be split into 397 soft engagements, 904 active engagements, 654 voting alerts and 379 pre-AGM dialogues. Amundi also indicate that they engaged with 1 364 unique companies in 2021. A second example of asset managers is Robeco, which is a Dutch asset manager with €200.7 bn in assets under

management at the end of 2021. They reported 270 engagement cases² (79 environmental issues, 76 social issues, 52 governance issues, 35 SDG issues and 28 global controversy issues), while the number of engagement activities was 942 including 393 conference calls, 402 written correspondence, and 4 physical meetings. Concerning asset owners, PGGM (Dutch pension fund with €293.5 bn in assets under management at the end of 2021), reported 154 company engagements in their 2021 integrated annual report³. A second example of asset owners is the Norway’s sovereign wealth fund, which managed €1.24 tn at the end of 2021. They held a total of 2,628 meetings with 1,163 companies⁴, and they had written communication with 486 companies in 2021. They also gave the breakdown by topics⁵: climate change (797), circular economy (190), biodiversity (48), ocean sustainability (18), etc.; children’s rights (40), data privacy (34), customer interests (129), etc.; effective boards (267), remuneration (183), protection of shareholders (68), etc. These four examples concern large investors, but small investors also communicate on their engagement policy. Platypus Asset Management, an Australian boutique firm with $5 bn in assets under management, conducted 66 one-on-one meetings on ESG issues in 2021. Their 2021 engagement report⁶ is very transparent since they listed the date of each meeting, the name of the company, the ESG issue and a summary of the meeting⁷.

---

⁵The sum is greater than 2,628, because several topics can be discussed during one meeting.
⁷For instance, on 9 June 2021, they met FPH on general governance. Here is the summary: “Discussed Fisher and Paykel’s approach to ESG including carbon — embodied emissions, very impressive science-based reduction targets including Scope 3, dovetails nicely with focus on product quality/need to scrutinise supply chain. The CEO is focused
Propose resolutions

According to the SEC (Securities Exchange Act Rule 14a-8, §240), “a shareholder proposal or resolution is a recommendation or requirement that the company and/or its board of directors take action, which the shareholder intend to present at a meeting of the company’s shareholders. The proposal should state as clearly as possible the course of action that the shareholder believes the company should follow. If the proposal is placed on the company’s proxy card, the company must also provide in the form of proxy means for shareholders to specify by boxes a choice between approval or disapproval, or abstention.” Generally, shareholder resolutions are opposed by the management. Nevertheless, all submitted proposals to the management are not necessarily accepted. In the US, if a company want to exclude a shareholder proposal, they can write a letter to the SEC explaining that the proposal violates one or more conditions of SEC Rule 14a-8 (Matsusaka et al., 2016). Shareholder resolutions can be excluded because of procedural requirements\(^8\) or substantive bases\(^9\). Then, the SEC may or not accept the exclusion. If the SEC accepts the exclusion, the company receives a “no-action” letter, indicating that the SEC will take no action if the company leaves the proposal out of the proxy statement\(^10\). In other countries, the filing of shareholder resolutions and the acceptance rules are different. In France, Germany and UK, shareholders can submit a draft resolution to the company if they own at least 5% of the capital. This threshold is equal to 2.5% in Italy, 0.33% in the Netherlands and 3% in Spain. If shareholders organise together, the rule is the same in France, Germany, Italy and the Netherlands. In Spain, there is no provision for shareholders to organise together. In the UK, they must represent 100 shareholders and at least £10,000 in investment.

A shareholder resolution can be viewed as an escalation in the context of failed engagement or a lack of responsiveness by the company. It is a way for investors to publicly display that they are not happy with the management. Nevertheless, even if the resolution is approved by a majority of shareholders, its implementation may be an issue. For instance, shareholder resolutions are not binding in the US. This is not the case in Europe, but the management of the company can always delay the implementation or consider a partial implementation. In this context, shareholder resolutions are more viewed as a negative signal or a dissent sent to the company and the market, especially when they get media coverage and attention. Nevertheless, voted shareholder resolutions on emissions and potential cost impact of the transition on the business. Also discussed gender diversity and modern slavery\(^7\).

\(^8\) The procedural requirements are described in Rules 14a-8(b)-(h): proponent must have held stock worth $2000 or 1% of firm value continuously for at least one year before submitting proposal and must continue to hold them through meeting date; proponent may only submit one proposal per meeting; proposal and supporting statement may not exceed 500 words; proposal must be submitted no less than 120 days before proxy statement is mailed; proponent or representative must be present at meeting (Matsusaka et al., 2016, Table 1).

\(^9\) The thirteen substantive bases are described in Rule 14a-8(i): improper subject for action under state law; will cause the company to violate state, federal, or foreign law to which it is subject; proposal and supporting statement are materially false or misleading; relates to redress of a personal claim or grievance, or be designed to provide a benefit to proponent that is not shared by the other shareholders at large; relates to operations that account for less than 5 percent of company assets or sales; company lacks the power to implement; deals with ordinary business operations; would disqualify a director candidate, remove a director from office, question competence of director or nominee; seek to include specific nominee, or otherwise affect the outcome of director election; conflicts with company’s own proposal; company has already substantially implemented proposal; substantially duplicates another proposal; deals with substantially the same subject as another proposal from previous years that received (specified) low support from shareholders; relates to specific amounts of dividends (Matsusaka et al., 2016, Table 1).

\(^10\) On page 3, we have seen that shareholders organized resolutions against the production of napalm during the Vietnam War. For instance, the Medical Committee for Human Rights filed a shareholder proposal in 1969 to force the Dow Chemical Company to stop its production of napalm. The SEC allowed Dow to exclude this shareholder proposal from its 1970 proxy voting, and therefore the proposal was not presented to the shareholders at the 1970 annual general meeting.
are exceptional. For example, we report below some figures\textsuperscript{11} for companies in the Russell 3000 index as of proxy season 2022 (from 1st June 2021 to 30 June 2022):

- 98\% of proposals are filed by the management, while less than 2\% corresponds to shareholder resolutions;
- Only 60\% of shareholder resolutions are voted; The other 40\% are omitted, not presented, withdrawn or pending;
- The average number of proposals per company is around two;
- The proponents of shareholder resolutions are concentrated on a small number of investors or organisations (15 proponents were responsible of 75\% of shareholder proposals);
- The repartition of shareholder proposals voted in 2022 was the following: 11\% related to E issues, 41\% related to S issues and 48\% related to G issues.

These figures show that there are few shareholder proposals and they are genially filed by the same group of investors. In fact, many shareholder proposals that are submitted to proxy voting are withdrawn following negotiations between shareholders and the management before the annual general meeting\textsuperscript{12}. Therefore, few investors have a true experience of an shareholder resolution that is voted during the AGM.

**Vote**

In just five years, voting at annual general meetings has become the norm for ESG investors. It is now considered as a fiduciary duty of asset owners and managers and the evidence that an investor is socially responsible. Today, voting choices are under scrutiny and are analyzed by many associations and NGOs. For instance, new editions of the Voting Matters series published by ShareAction\textsuperscript{13} are very much awaited with fear and apprehension by asset managers.

The voting landscape has evolved considerably these last years, especially in Europe. In the US, there is a long history that mutual funds vote at general meetings, because the SEC has always seen voting as one of the main fiduciary duties of collective funds\textsuperscript{14}. This explains that US mutual funds have a higher voting participation than European mutual funds. In fact, the ESG fad has changed in many different ways the activity of voting, which is now one of the priorities from investors. First, the gap between asset owners and asset managers has been considerably reduced whereas the voting participation of asset managers was poor ten years ago (Brière et al., 2020). Second, voting infrastructures have been strongly developed in Europe, while they exist in the US for many

\textsuperscript{11}We use the reports of Rosati et al. (2022) and Tonello (2022).
\textsuperscript{12}An example can be found in the 2021 Stewardship report of Robeco: "At the end of 2020, we filed a shareholder resolution at ADM’s 2021 shareholder meeting, asking the company to step up its efforts to eliminate deforestation in its soy supply chain. After several weeks of intense negotiations, spanning across multiple meetings with ADM’s head of sustainability and corporate secretary, we managed to get the company to agree to most of our key requests and so we withdrew the proposal. Our achievement was to ensure that ADM published a revised no-deforestation policy, and committed to eliminate deforestation from all its supply chains by 2030." (Robeco, 2021, page 32). ADM is a company specialized in food, pet and animal nutrition. Other examples can be found in the stewardship report of Amundi, Candriam, Groupama Asset Management, etc.
\textsuperscript{13}ShareAction is a UK-based registered charity that promotes responsible investment.
\textsuperscript{14}You may consult the speech “Every Vote Counts: The Importance of Fund Voting and Disclosure” by the Commissioner Allison Herren Lee at the 2021 ICI Mutual Funds and Investment Management Conference (March 17, 2021), www.sec.gov/news/speech/lee-every-vote-counts.
years. Nevertheless, the proxy advisory market is dominated by two US proxy advisory agencies (Institutional Shareholder Services or ISS, and Glass Lewis), that represent 97% of the market.

Third, asset managers have a high pressure to vote if they want to be credible. Voting has become a central pillar of any responsible investment policies, and it is now part of the ESG credentials when asset owners select asset managers.

In 2002, the United Kingdom adopt a legislation requiring companies to allow the shareholders to have a mandatory but non-binding vote on the executive compensation at each annual general meeting. This concept is called say on pay. According to (Rosati et al., 2022), results for 2022 season has showed an increasing of shareholder opposition on this topic. For instance, support for executive remuneration was equal to 87% for Russell 3000 companies in 2022 compared to 89% in 2021. The lowest value was reached by Norwegian Cruise Line Holdings with only 15.4% of votes for.

In Europe, we observe the same phenomenon. In Germany, 25% of say on pay votes were contested. In France and Spain, the most contested resolution was remuneration policy proposals. For example, about 50% of say on pay resolutions received at least 10% shareholder resolution of France. To have a point of comparison, the average support rate for management proposals is generally very high and greater than 95%.

Say on climate is inspired by say on pay proposals. This initiative was launched by the hedge fund activist investor Chris Hohn through the Children’s Investment Fund Foundation (CIFF) in 2020. Since then, it has 54 investor members ($14 tn AUM) such as Boussard & Gavaudan, CDPQ, Oxford University Endowment Management, Sarasin & Partners, Soros Fund Management or TCI Fund Management, and it is supported by CIFF, CDP, ShareAction and the Australasian Centre for Corporate Responsibility (ACRR). More generally, say on climate is any shareholder or management resolution on the climate strategy of the company. When it is filed by the company’s management, they expect that shareholders will vote for (shareholder approval of the climate strategy). When it is filed by shareholders, the resolution is against the climate strategy of the company. In 2021, 26 companies have submitted a climate strategy at their annual general meetings and there were 88

---


16 The website is [www.sayonclimate.org](http://www.sayonclimate.org).

17 19 were at European companies (3 in France, 5 in Spain, 1 in Switzerland and 10 in the UK), 3 in North America (1 in Canada and 2 in the US), 3 in South Africa and 1 in Australia.

18 In 2022, the number of companies has increased and reached 36. Among them, we find seven oil & gas companies
climate-related shareholder proposals that were voted (ISS Governance, 2022). The average support rate was 93% for resolutions filed by the company and 32.7% when resolutions have been proposed by shareholders.

As we have previously seen, there are few shareholder proposals per company. The number of voted shareholder proposals is even more smaller. For instance, there were only 555 shareholder resolutions that have been voted in 2022 among the Russell 3000 companies, meaning less than 1 resolution for 5 companies. In Figure 6.4, we have reported the average support rate. In 2022, it is less than 40% for governance topics and it falls to 29% for environmental and social issues. Finally, the number of voted proposals receiving majority support is equal to 82. This means that there was one shareholder resolution that was adopted for 37 companies. Therefore, we may question the impact and the effectiveness of vote. This explains that vote is another form of voice for many academics.

![Figure 6.4: Average support rate of shareholder proposals (Russell 3000 companies)](image)

Source: PwC’s Governance Insights Center (2022).

If we focus on the year 2022 and the US, the main topics of shareholder proposals were emissions reduction targets and scope 3 inclusion for the E pillar, diversity, civil rights and racial equity audits, human rights and workforce harassment for the S pillar, and executive compensation and political lobbying for the G pillar (Rosati et al., 2022). In Europe, most of shareholder resolutions concern the remuneration of the management.

**Remark 46** The voting behavior of asset managers is analyzed in Section 6.2.4 on page 241.

(BP, Equinor, Repsol, Santos, Shell, TotalEnergies, Woodside Petroleum).

_Handbook of Sustainable Finance_
Voice

The term voice has been popularized in 1970 by the economist Albert Hirschman, when he published its book “Exit, Voice, and Loyalty: Responses to Decline in Firms, Organizations, and States”. The book states that members of an organization have two main possible responses when they consider that the organization fails. They can exit (withdraw from the relationship) or they can voice (change the relationship through communication of the complaint). From a socio-economic viewpoint, exit is associated with Adam Smith’s invisible hand while voice is by nature political and may be confrontational. The exit-voice model of Hirschman (1970) can be applied to many situations: protest movements, migration, class action, and even corporate governance (Kostant, 1999).

In the theory of shareholder activism, voice may refer to several forms of engagement, for instance engage behind the scenes or propose resolutions (Edmans, 2014). In this chapter, voice refers to a situation where the communication between activist shareholders and the company becomes public. Like resolution proposals, voice can be interpreted as a form of escalation. Indeed, the debate and the disagreement become publicly known, implying that other stakeholders are informed and can participate, e.g., other shareholders, media, politics and the society. The company faces then the risk to be placed in the political spotlight and respond to public criticism and scrutiny. The situation can become uncomfortable for the company, especially when non-technical stakeholders (media and the society) look at the issue.

According to McCahery et al. (2016), voice is rarely used by individual institutional investors. One of the reason is that public communications may be ineffective, justifying the prevalence of behind the scenes communications (Levit, 2019). However, voice has increased during the recent...
years due to two main factors. The first one is that collaborative engagement between investors are now quite common thanks to initiatives such as PRI or Climate Action 100+. In this context, they require more transparency by tracking progress of each member. For instance, when signing on to the initiative Climate Action 100+, investors are asked to nominate which focus companies they wish to engage with and whether this is as a lead investor or collaborating investor. The second factor is the increasing involvement of NGOs in the debate on engagement and greenwashing\textsuperscript{19}. In this context, investors must sometimes publicly answer to greenwashing suspicions or allegations for supporting and financing some companies that are considered by these NGOs as detrimental to the environment or harmful to human health. All these elements explain why voice against companies, but also voice against investors, has recently gained in importance.

**Initiate a takeover**

Acquiring a large proportion of the company’s shares is an agressive form of shareholder activism. The underlying idea is to form a coalition with other large shareholders in order to obtain a board set and to ultimately control the company’s board. This strategy is typically implemented by activist hedge funds (Gantchev, 2013). Generally, managers perceive activist events as a hostile act, because their compensation and job security are threatened Gantchev \textit{et al.} (2019). Most of the time, this form of shareholder activism has a big impact on the firm (change in business strategy, implementation of the proposed solutions, etc.). Nevertheless, it has never been used by ESG investors. Therefore, it is solely motivated by financial underperformance, and not extra-financial issues.

**Exit**

Exit refers to the process of selling off investments in a particular company or industry. Divestment is a more general term that implies a significant exposure reduction. In this case, we speak about partial divestment while exit corresponds to a full divestment\textsuperscript{20}. For example, investors may decide to divest from a company if they are not satisfied with its ESG performance, in particular if the company policy implies social issues or it does not take sufficient action to address environmental concerns. Investors may also decide to divest from a sector such as fossil fuels or tobacco. Therefore, the exit policy is related to two ESG investing strategies\textsuperscript{21}: exclusion and norms-based screening. Nevertheless, divestment could not be equated to these ESG strategies. Indeed, the divestment/exit concept implies that investors are currently invested in the company and they decide to sell their participation, because they are not agreed with the ESG policy of the firm. In this context, divestment is the ultimate engagement action, meaning that investors believe that they can not influence the company’s behavior by staying invested. In this case, divestment is “the final step in an escalation strategy” (PRI, 2022a) and may be viewed as a failure of the engagement action on the part of investors. When it concerns an industry, divestment can be motivated because there are high risks or poor opportunities that the industry transition to a more sustainable business model. For example, divesting from coal reserves or mining sector may reduce the exposure of investors to the risk of stranded assets\textsuperscript{22}. As we have seen in the first chapter, exit can also be motivated by moral values. In this case, it coincide with the norms-based screening strategy.

\textsuperscript{19}For instance, we can cite the following examples among others: As You Sow, Citizens’ Climate Lobby, Climate Alliance, Friends of the Earth, Fund Our Future, Oxfam, Reclaim Finance and Sunrise Movement.

\textsuperscript{20}Nevertheless, we notice that the two terms are often used interchangeably.

\textsuperscript{21}These strategies are described on page 40.

\textsuperscript{22}Stranded assets are studied in Section 10.2 on page 505.
Box 6.1: Case study: the Cambridge University endowment fund

In their research paper “To Divest or to Engage? A Case Study of Investor Responses to Climate Activism”, Chambers et al. (2020) studied the interesting case study of the Cambridge University endowment fund:

“A dilemma faced by an increasing number of investors is whether to divest from environmentally damaging businesses or whether to enter into a dialogue with them. This predicament now has its epicentre in Cambridge, England, where the ancient University of Cambridge faces great pressure from students and staff to respond to the threat of climate breakdown. Having already received two reports on its approach to responsible investment, the university has appointed a new chief investment officer (CIO) who, alongside University Council and the wider university community, needs to consider the question of whether to divest from or to engage with fossil-fuel firms.”

This paper tells the story of the Cambridge’s fossil-fuel divestment movement from 2012 to 2020. This includes the creation of the Positive Investment Cambridge group, the establishment of the Ethical Investment Working Group, the publication of several reports, many Zero Carbon Society petitions in favour of fossil fuel divestment, the formation of the Divestment Working Group, the activism of students and faculty staff, the involvement of many respected scholars, including prestigious professors (e.g., astronomer Royal officer, Nobel laureate, chief scientific adviser, distinguished statisticians, Fields medallists, fellows of the Royal Academy and the Royal Society), etc. The research paper reveals how pressures upon institutional investors to respond to climate activism can accelerate. It concludes that “investment professionals need to understand the forces for change”, “a head-in-the-sand response is counter-productive” and “changes in investment policy should be evidence-based”.

The case of fossil fuel sector is certainly the most symbolic divestment theme. According to the Global Divestment Commitments Database, about 1500 institutions have committed to divest from fossil fuels as of October 2021. In Figure 6.6, we report the break-down by types of organization. The three most important categories are faith-based organizations, educational institutions and philanthropic foundations, representing 63.10% of institutions divesting. They are followed by pension funds. Commitments can be classified into four categories: (1) thermal coal only, (2) coal and tar sands, (3) partial divestment from some but not all types of fossil fuel companies, (4) full divestment from any fossil fuel company (thermal coal, oil, gas). Some investors are already “fossil free”, meaning that they currently have no investment in fossil fuel companies and are committed to avoid any fossil fuel investments in the future. The debate on fossil fuel divestment is tough, because it is not only an investor debate, but also a matter of society. In Box 6.1, we report the tense relationship between the two sides. We notice that the choice to divest or not can be motivated by other considerations than rational evidence. The pressure of anti-fossil fuel movements may be one factor, the fear of greenwashing is another one. Moreover, “exit relaxes the tension between the activist and the board” (Levit, 2019). In some ways, exit is a comfortable position. The investor can continue to communicate with the company, but the situation is completely different. Before exit,

---

23 Including Axa Insurance, La Banque Postale, Harvard University, the State of Maine, the Norwegian Sovereign Wealth Fund, and the University of Oxford.
the investor has to convince the company to move. After exit, the company must prove that they will change and they must convince the investor to come back. Therefore, the roles are reversed.

Figure 6.6: What kinds of institutions are divesting from fossil fuel?

![Pie chart showing divestment percentages by type of institution.]

We have already seen that vote is a form of voice. For Admati and Pfleiderer (2009), exit is a form of voice too. Most of academic studies show that the impact of exit is mixed, because the cost of divestment may be high and its effectiveness is limited (Jahnke, 2019; Levit, 2019; Broccardo et al., 2022; Edmans et al., 2022). For some academics, the impact of divestment may also be negative:

“Large divestment campaigns are undertaken in part to depress share prices of firms that investors see as engaged in harmful activities. We show that, if successful, investors who divest earn lower and riskier returns than those that do not, leading them to control a decreasing share of wealth over time. Divestment therefore has only a temporary price impact. Further, we show that, for standard managerial compensation schemes, divestment campaigns actually provide an incentive for executives to increase, not reduce, the harm that they create. Therefore, divestment is both counter-productive in the short run, and self-defeating in the long run.” (Davies and Van Wesep, 2018, page 558).

In fact, we must distinguish the impact on primary and secondary markets. From a theoretical viewpoint, divestment decreases the price of the company share price on the secondary market, implying that the returns increase. On the primary market, this induces a higher cost of capital because of the lower demand. Therefore, the rationale for exit is the effect on the cost of capital. Nevertheless, it is difficult to verify empirically this effect in the last 10 years. Academics are more consensual when they study the impact before the exit. Indeed, according to Edmans (2009), the threat of exit has more impact than divestment itself, and “the power of loyalty relies on the threat of exit”. Again, we see that voice and exit are complementary instead of being mutually exclusive.
Box 6.2: Case studies of fossil fuel divestment

Church of England Pensions Board
By the end of 2021, the CoE Pensions Board was responsible for almost £3.7 bn of assets across three pension schemes. In July 2018, the General Synod of the Church of England voted on a motion to ensure that by 2023 the CoE pension funds have divested from fossil fuel companies that are not prepared to align with the goals of the Paris Agreement. In 2020, they engaged with 21 companies. At the end of the process, 12 companies were supposed to make sufficient progress, while 9 companies were added to the list of restricted investments. These divestments totalled £32.23 mn.


The Universities Superannuation Scheme (USS)
The Universities Superannuation Scheme (USS) is the pension scheme for university staff in the UK. They manage about £90 bn. In 2020, USS undertook a review of sectors in which the scheme invests. They concluded that, in several cases, the outcomes predicted by the market did not appropriately consider the potential financial impact of certain specific risks, including ESG. As a result, they excluded certain sectors: tobacco manufacturing; thermal coal mining (coal to be burned for electricity generation), specifically where they made up more than 25% of revenues, and certain controversial weapons. The first exclusion was announced in May 2020. Two years after, divestment from these sectors is completed. According to Ethics for USS (a group of USS members committed to reforming USS and ensuring an investment strategy that protects the planet, respects human rights, invests responsibly and ensures good pensions), “USS still has large investments in the industries responsible for the climate emergency [...], while they recognise that USS has made plans to decarbonise its investment portfolio”. Ethics for USS estimated that “USS continue to invest £570 mn in 48 leading fossil fuels companies”, and USS should extend its divestment policy “to include other companies that have not committed to a credible path towards zero emissions”.


6.1.3 Individual versus collaborative engagement
Academic references are Dimson et al. (2021).

6.1.4 The role of institutional investors
Academic references are Appel et al. (2016), Krueger et al. (2020), Chen et al. (2020) and Gillan and Starks (2000).

6.1.5 Impact of active ownership
Academic references are Dimson et al. (2015), Grewal et al. (2016), and Broccardo et al. (2022).
6.2 ESG voting

6.2.1 Voting process

Each country has its own voting process. Nevertheless, they share some common ground. According to NBIM (2020), they typically include the following steps:

- “The company sets the agenda for the annual shareholder meeting;
- The custodian confirms the identity of the shareholders and the number of shares eligible for voting — often for a specific date ahead of the meeting (record date);
- Shareholders receive the meeting materials from the company (may be before or after the record date);
- Shareholders procuring proxy advisory services receive voting recommendations;
- Shareholders instruct the custodian on how to vote, often through a proxy voting service provider, within a deadline ahead of the shareholder meeting (cut-off date);
- Voting takes place at the shareholder meeting;
- Shareholders receive confirmation from the service provider that their voting instructions have been carried out.”

6.2.2 Proxy voting


6.2.3 Defining a voting policy

6.2.4 Statistics about ESG voting

In this section, we analyze the behavior of investors when they vote ESG resolutions. In the case of asset managers, we use the annual reports published by ShareAction. For asset owners, we use various surveys and complete the assessment by studying engagement reports of some pension funds.

Asset managers

ShareAction started the Voting Matters series in 2019. At that time, the report reviewed how largest asset managers have voted on shareholder resolutions linked to climate change (ShareAction, 2019). In 2020 and 2021, they extended the analysis by including the S pillar in addition to the E pillar (ShareAction, 2020, 2021). Finally, the 2022 edition analyzed shareholder-filed governance resolutions that directly relate executive compensation and political spending policies to environmental and social issues (ShareAction, 2023). After having merged the four datasets and clean the data, we obtain a database with 84 unique asset managers with the following frequencies: 35 in 2019, 54 in 2020, 65 in 2021 and 68 in 2022. There is only 26 asset managers, which are present every year. The scores calculated by ShareAction were based on 65 selected shareholder proposals in 2019, 102 in 2020, 146 in 2021 and 252 in 2022. In Table 6.1, we report some statistics of the selected shareholder resolutions. Let $s_j$ be the support rate of resolution $j$. The resolution has the majority support if $s_j \geq 50\%$. For instance, among the 64 shareholder proposals in 2019, only three have obtained the majority, implying a success rate of 4.7%. During the period 2019–2022, this success rate is around 15%. We have also reported the 10%, 25%, 75% and 90% percentiles. The interquartile range is between 12% and 43%. Finally, we notice that the average support rate is greater for environmental resolutions than for social resolutions.

<table>
<thead>
<tr>
<th>Year</th>
<th>2019</th>
<th>2020</th>
<th>2021</th>
<th>2022</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of resolutions</td>
<td>64</td>
<td>102</td>
<td>144</td>
<td>249</td>
</tr>
<tr>
<td>Resolutions with majority support</td>
<td>3</td>
<td>15</td>
<td>29</td>
<td>37</td>
</tr>
<tr>
<td>Success rate (in %)</td>
<td>4.7</td>
<td>14.7</td>
<td>20.1</td>
<td>14.9</td>
</tr>
<tr>
<td>Average support rate (in %)</td>
<td>28.2</td>
<td>29.9</td>
<td>32.9</td>
<td>29.9</td>
</tr>
<tr>
<td>10%</td>
<td>6.5</td>
<td>9.2</td>
<td>7.2</td>
<td>9.4</td>
</tr>
<tr>
<td>25%</td>
<td>17.0</td>
<td>13.1</td>
<td>12.0</td>
<td>13.5</td>
</tr>
<tr>
<td>75%</td>
<td>37.7</td>
<td>42.6</td>
<td>42.8</td>
<td>40.3</td>
</tr>
<tr>
<td>90%</td>
<td>41.8</td>
<td>55.2</td>
<td>81.2</td>
<td>57.6</td>
</tr>
<tr>
<td>Percentile of support rate (in %)</td>
<td>28.2</td>
<td>35.8</td>
<td>41.8</td>
<td>31.6</td>
</tr>
<tr>
<td>Average support rate (in %)</td>
<td>24.5</td>
<td>28.8</td>
<td>27.4</td>
<td></td>
</tr>
</tbody>
</table>


For each asset manager, the support rate is calculated as:

$$\text{support rate} = \frac{\# \{\text{for}\}}{\# \{\text{for} + \text{against} + \text{abstention} + \text{dit-not-vote} + \text{split-vote}\}}$$

24In particular, some asset managers have merged or changed their name.
25They are APG AM, AXA IM, Abrdn, Allianz GI, Amundi AM, BNP PAM, BlackRock, Capital Group, DWS, Fidelity Investments, Generali Insurance AM, Goldman Sachs AM, HSBC Global AM, Invesco, J.P. Morgan AM, Legal & General, M&G IM, Ninety One, Northern Trust AM, Nuveen AM, SSGA, Schroders, T. Rowe Price, UBS AM, Vanguard, and Wellington Management.
26Some resolutions are excluded from the analysis because we don’t have the figures.
27See Figure 6.7 for the empirical histogram.
In Table 6.2, we compute the average support rate of shareholder resolutions with two methods. The arithmetic mean is the simple average with respect to all asset managers, while the contribution of each asset manager is proportional to its assets under management for the weighted mean. We observe that the arithmetic mean of the support rates increases continuously since 2019 if we consider the overall score and the S pillar. This is not true for the E pillar for which we observe a lower value in 2022 compared to 2021. Moreover, the figure of 65% that we found in 2022 for the overall score is due to the introduction of the pay & politics topic. If we focus on the weighted mean, the figures are lower. For instance, the average support rate in 2022 is equal to 46.5% instead of 65%. This means that largest asset managers are voting for shareholder resolutions less than the others.

<table>
<thead>
<tr>
<th>Topic</th>
<th>Method</th>
<th>2019</th>
<th>2020</th>
<th>2021</th>
<th>2022</th>
</tr>
</thead>
<tbody>
<tr>
<td>Overall</td>
<td>Arithmetic</td>
<td>45.8</td>
<td>57.4</td>
<td>58.9</td>
<td>65.0</td>
</tr>
<tr>
<td></td>
<td>Weighted</td>
<td>32.7</td>
<td>42.1</td>
<td>47.6</td>
<td>46.5</td>
</tr>
<tr>
<td>Environment</td>
<td>Arithmetic</td>
<td>45.8</td>
<td>61.0</td>
<td>66.0</td>
<td>64.8</td>
</tr>
<tr>
<td></td>
<td>Weighted</td>
<td>32.7</td>
<td>44.7</td>
<td>55.8</td>
<td>48.8</td>
</tr>
<tr>
<td>Social</td>
<td>Arithmetic</td>
<td>53.3</td>
<td>55.2</td>
<td>62.7</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Weighted</td>
<td>39.0</td>
<td>43.7</td>
<td>44.3</td>
<td></td>
</tr>
<tr>
<td>Pay &amp; politics</td>
<td>Arithmetic</td>
<td>71.5</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Weighted</td>
<td></td>
<td></td>
<td></td>
<td>47.8</td>
</tr>
</tbody>
</table>

Chapter 6. Engagement & Voting Policy

Figure 6.8: Arithmetic average support rate in % per country and year

Overall

Environment

Social

Pay


Figure 6.9: Weighted average support rate in % per country and year

Overall

Environment

Social

Pay

If we perform a region analysis (Figures 6.8 and 6.9), we observe the following facts. British and European\(^{28}\) asset managers have a similar voting behavior. Their support rate is significantly greater than this found in the US. Nevertheless, American asset managers have improved their ESG voting policy in 2020 and 2021, which explains the increase of the overall score for the world. In 2022, the increase of the European support was offset by the American setback.

### Table 6.3: Best performers (2022, overall)

<table>
<thead>
<tr>
<th>Rank</th>
<th>Name</th>
<th>Country</th>
<th>AUM</th>
<th>Overall</th>
<th>G</th>
<th>E</th>
<th>S</th>
<th>Pay</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Achmea IM</td>
<td>Netherlands</td>
<td>251</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>2</td>
<td>Impax AM</td>
<td>UK</td>
<td>56</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>3</td>
<td>BNP PAM</td>
<td>France</td>
<td>761</td>
<td>99</td>
<td>97</td>
<td>100</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>4</td>
<td>MN</td>
<td>Netherlands</td>
<td>193</td>
<td>99</td>
<td>97</td>
<td>100</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>5</td>
<td>Candriam</td>
<td>Luxembourg</td>
<td>180</td>
<td>98</td>
<td>97</td>
<td>99</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>6</td>
<td>PGGM</td>
<td>Netherlands</td>
<td>531</td>
<td>97</td>
<td>95</td>
<td>100</td>
<td>97</td>
<td>97</td>
</tr>
<tr>
<td>7</td>
<td>Man</td>
<td>UK</td>
<td>149</td>
<td>96</td>
<td>98</td>
<td>94</td>
<td>98</td>
<td>98</td>
</tr>
<tr>
<td>8</td>
<td>Robeco</td>
<td>Netherlands</td>
<td>228</td>
<td>95</td>
<td>94</td>
<td>100</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>9</td>
<td>Aviva Investors</td>
<td>UK</td>
<td>363</td>
<td>93</td>
<td>88</td>
<td>96</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>10</td>
<td>Amundi AM</td>
<td>France</td>
<td>2 348</td>
<td>93</td>
<td>93</td>
<td>92</td>
<td>98</td>
<td>98</td>
</tr>
<tr>
<td>11</td>
<td>Nordea AM</td>
<td>Finland</td>
<td>333</td>
<td>91</td>
<td>93</td>
<td>89</td>
<td>90</td>
<td>90</td>
</tr>
<tr>
<td>12</td>
<td>Aegon AM</td>
<td>Netherlands</td>
<td>466</td>
<td>90</td>
<td>85</td>
<td>94</td>
<td>90</td>
<td>90</td>
</tr>
<tr>
<td>13</td>
<td>Federated Hermes</td>
<td>UK</td>
<td>672</td>
<td>89</td>
<td>88</td>
<td>87</td>
<td>90</td>
<td>90</td>
</tr>
<tr>
<td>14</td>
<td>Pictet AM</td>
<td>Switzerland</td>
<td>284</td>
<td>88</td>
<td>85</td>
<td>90</td>
<td>91</td>
<td>91</td>
</tr>
<tr>
<td>15</td>
<td>Legal &amp; General</td>
<td>Switzerland</td>
<td>1 923</td>
<td>86</td>
<td>84</td>
<td>84</td>
<td>98</td>
<td>98</td>
</tr>
</tbody>
</table>

Source: ShareAction (2023) & Author’s calculations.

In Tables 6.3 and 6.4, we report the ranking of the best fifteen and worst ten asset managers when we consider the 2022 overall score. For each row, we indicate the rank, the name, the country, the assets under management (in $ bn) and the 2022 scores expressed in percentage. Two asset managers obtain a score of 100%: Achmea Investment Management and Impax Asset Management Group. The Top 15 ranking is dominated by asset managers located in the Netherlands, the UK and France, whereas there are seven American asset managers in the Bottom 10.

### Table 6.4: Worst performers (2022, overall)

<table>
<thead>
<tr>
<th>Rank</th>
<th>Name</th>
<th>Country</th>
<th>AUM</th>
<th>Overall</th>
<th>G</th>
<th>E</th>
<th>S</th>
<th>Pay</th>
</tr>
</thead>
<tbody>
<tr>
<td>59</td>
<td>Goldman Sachs AM</td>
<td>US</td>
<td>2 218</td>
<td>35</td>
<td>56</td>
<td>24</td>
<td>24</td>
<td>24</td>
</tr>
<tr>
<td>60</td>
<td>Baillie Gifford</td>
<td>UK</td>
<td>455</td>
<td>31</td>
<td>29</td>
<td>29</td>
<td>45</td>
<td>45</td>
</tr>
<tr>
<td>61</td>
<td>SSGA</td>
<td>US</td>
<td>4 140</td>
<td>29</td>
<td>30</td>
<td>31</td>
<td>22</td>
<td>22</td>
</tr>
<tr>
<td>62</td>
<td>BlackRock</td>
<td>US</td>
<td>10 014</td>
<td>24</td>
<td>28</td>
<td>24</td>
<td>15</td>
<td>15</td>
</tr>
<tr>
<td>63</td>
<td>T. Rowe Price</td>
<td>US</td>
<td>1 642</td>
<td>17</td>
<td>26</td>
<td>11</td>
<td>18</td>
<td>18</td>
</tr>
<tr>
<td>64</td>
<td>Fidelity Investments</td>
<td>US</td>
<td>4 520</td>
<td>17</td>
<td>23</td>
<td>19</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>65</td>
<td>Vanguard</td>
<td>US</td>
<td>8 274</td>
<td>10</td>
<td>12</td>
<td>9</td>
<td>9</td>
<td>9</td>
</tr>
<tr>
<td>66</td>
<td>Dimensional Fund Advisors</td>
<td>US</td>
<td>679</td>
<td>4</td>
<td>6</td>
<td>5</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>67</td>
<td>Santander AM</td>
<td>Spain</td>
<td>220</td>
<td>4</td>
<td>0</td>
<td>5</td>
<td>6</td>
<td>6</td>
</tr>
<tr>
<td>68</td>
<td>Walter Scott &amp; Partners</td>
<td>UK</td>
<td>95</td>
<td>3</td>
<td>0</td>
<td>6</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

Source: ShareAction (2023) & Author’s calculations.

\(^{28}\)This includes the following countries: Finland, France, Germany, Italy, Luxembourg, Netherlands, Spain, Sweden and Switzerland.
Table 6.5: Ranking of the 25 largest asset managers (2022, overall)

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>22</td>
<td>BlackRock</td>
<td>US</td>
<td>10014</td>
<td>7</td>
<td>12</td>
<td>40</td>
<td>24</td>
<td>11</td>
<td>53</td>
<td>28</td>
<td>12</td>
<td>34</td>
<td>24</td>
<td>15</td>
</tr>
<tr>
<td>25</td>
<td>Vanguard</td>
<td>US</td>
<td>8274</td>
<td>8</td>
<td>14</td>
<td>26</td>
<td>10</td>
<td>15</td>
<td>38</td>
<td>12</td>
<td>12</td>
<td>20</td>
<td>9</td>
<td>9</td>
</tr>
<tr>
<td>23</td>
<td>Fidelity Investments</td>
<td>US</td>
<td>4520</td>
<td>9</td>
<td>31</td>
<td>29</td>
<td>17</td>
<td>20</td>
<td>23</td>
<td>23</td>
<td>44</td>
<td>33</td>
<td>19</td>
<td>2</td>
</tr>
<tr>
<td>21</td>
<td>SSGA</td>
<td>US</td>
<td>4140</td>
<td>26</td>
<td>35</td>
<td>32</td>
<td>29</td>
<td>40</td>
<td>42</td>
<td>30</td>
<td>29</td>
<td>27</td>
<td>31</td>
<td>22</td>
</tr>
<tr>
<td>18</td>
<td>J.P. Morgan AM</td>
<td>US</td>
<td>2742</td>
<td>7</td>
<td>43</td>
<td>37</td>
<td>37</td>
<td>51</td>
<td>50</td>
<td>43</td>
<td>34</td>
<td>31</td>
<td>25</td>
<td>53</td>
</tr>
<tr>
<td>16</td>
<td>Capital Group</td>
<td>US</td>
<td>2716</td>
<td>5</td>
<td>8</td>
<td>28</td>
<td>45</td>
<td>12</td>
<td>26</td>
<td>37</td>
<td>4</td>
<td>31</td>
<td>47</td>
<td>58</td>
</tr>
<tr>
<td>2</td>
<td>Amundi AM</td>
<td>France</td>
<td>2348</td>
<td>66</td>
<td>89</td>
<td>93</td>
<td>93</td>
<td>91</td>
<td>97</td>
<td>93</td>
<td>88</td>
<td>90</td>
<td>92</td>
<td>98</td>
</tr>
<tr>
<td>20</td>
<td>Goldman Sachs AM</td>
<td>US</td>
<td>2218</td>
<td>37</td>
<td>45</td>
<td>47</td>
<td>35</td>
<td>48</td>
<td>57</td>
<td>56</td>
<td>43</td>
<td>40</td>
<td>24</td>
<td>24</td>
</tr>
<tr>
<td>3</td>
<td>Legal &amp; General</td>
<td>UK</td>
<td>1923</td>
<td>82</td>
<td>96</td>
<td>77</td>
<td>86</td>
<td>96</td>
<td>87</td>
<td>84</td>
<td>95</td>
<td>73</td>
<td>84</td>
<td>98</td>
</tr>
<tr>
<td>24</td>
<td>T. Rowe Price</td>
<td>US</td>
<td>1642</td>
<td>5</td>
<td>22</td>
<td>31</td>
<td>17</td>
<td>27</td>
<td>44</td>
<td>26</td>
<td>17</td>
<td>25</td>
<td>11</td>
<td>18</td>
</tr>
<tr>
<td>15</td>
<td>Invesco</td>
<td>US</td>
<td>1611</td>
<td>34</td>
<td>37</td>
<td>37</td>
<td>47</td>
<td>52</td>
<td>51</td>
<td>54</td>
<td>19</td>
<td>28</td>
<td>37</td>
<td>61</td>
</tr>
<tr>
<td>12</td>
<td>Morgan Stanley IM</td>
<td>US</td>
<td>1566</td>
<td>55</td>
<td>64</td>
<td>59</td>
<td>64</td>
<td>59</td>
<td>64</td>
<td>64</td>
<td>53</td>
<td>65</td>
<td>63</td>
<td>63</td>
</tr>
<tr>
<td>14</td>
<td>Wellington Management</td>
<td>US</td>
<td>1426</td>
<td>10</td>
<td>51</td>
<td>44</td>
<td>48</td>
<td>62</td>
<td>60</td>
<td>63</td>
<td>39</td>
<td>37</td>
<td>41</td>
<td>36</td>
</tr>
<tr>
<td>7</td>
<td>Northern Trust AM</td>
<td>US</td>
<td>1348</td>
<td>21</td>
<td>70</td>
<td>60</td>
<td>83</td>
<td>79</td>
<td>68</td>
<td>83</td>
<td>59</td>
<td>57</td>
<td>78</td>
<td>96</td>
</tr>
<tr>
<td>13</td>
<td>Nuveen AM</td>
<td>US</td>
<td>1271</td>
<td>62</td>
<td>63</td>
<td>56</td>
<td>59</td>
<td>71</td>
<td>76</td>
<td>57</td>
<td>56</td>
<td>48</td>
<td>52</td>
<td>79</td>
</tr>
<tr>
<td>8</td>
<td>UBS AM</td>
<td>Switzerland</td>
<td>1216</td>
<td>90</td>
<td>79</td>
<td>75</td>
<td>83</td>
<td>91</td>
<td>72</td>
<td>84</td>
<td>67</td>
<td>75</td>
<td>80</td>
<td>87</td>
</tr>
<tr>
<td>4</td>
<td>DWS</td>
<td>Germany</td>
<td>1055</td>
<td>74</td>
<td>66</td>
<td>85</td>
<td>86</td>
<td>66</td>
<td>92</td>
<td>86</td>
<td>65</td>
<td>80</td>
<td>80</td>
<td>100</td>
</tr>
<tr>
<td>10</td>
<td>AXA IM</td>
<td>France</td>
<td>1009</td>
<td>79</td>
<td>71</td>
<td>55</td>
<td>73</td>
<td>85</td>
<td>72</td>
<td>69</td>
<td>55</td>
<td>45</td>
<td>68</td>
<td>95</td>
</tr>
<tr>
<td>6</td>
<td>Schroders</td>
<td>UK</td>
<td>991</td>
<td>56</td>
<td>62</td>
<td>73</td>
<td>85</td>
<td>63</td>
<td>78</td>
<td>81</td>
<td>60</td>
<td>70</td>
<td>87</td>
<td>87</td>
</tr>
<tr>
<td>17</td>
<td>Alliance Bernstein</td>
<td>US</td>
<td>779</td>
<td>43</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>Allianz GI</td>
<td>Germany</td>
<td>766</td>
<td>89</td>
<td>81</td>
<td>77</td>
<td>86</td>
<td>89</td>
<td>81</td>
<td>80</td>
<td>73</td>
<td>76</td>
<td>91</td>
<td>85</td>
</tr>
<tr>
<td>1</td>
<td>BNP PAM</td>
<td>France</td>
<td>761</td>
<td>48</td>
<td>72</td>
<td>98</td>
<td>99</td>
<td>65</td>
<td>96</td>
<td>97</td>
<td>80</td>
<td>99</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>19</td>
<td>Columbia Threadneedle</td>
<td>US</td>
<td>754</td>
<td>37</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>25</td>
</tr>
<tr>
<td>9</td>
<td>Manulife IM</td>
<td>Canada</td>
<td>723</td>
<td>75</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>68</td>
</tr>
<tr>
<td>11</td>
<td>APG AM</td>
<td>Netherlands</td>
<td>721</td>
<td>72</td>
<td>70</td>
<td>59</td>
<td>72</td>
<td>80</td>
<td>65</td>
<td>89</td>
<td>59</td>
<td>56</td>
<td>57</td>
<td>83</td>
</tr>
</tbody>
</table>

If we focus on the largest asset managers, we obtain the 2022 ranking reported in Table 6.5. For each row, we indicate the rank according to the 2022 overall score, the name, the country, the assets under management (in $ bn) as of December 2022, the overall scores expressed in percentage for the four reporting years (2019 to 2022). We also report the thematic scores (environmental, social, and pay & politics). In this case, the six best performers are BNP Paribas Asset Management, Amundi, Legal & General, DWS, Allianz GI and Schroders (respectively two British, French and German asset managers). We also observe that some asset managers have made large improvement. For instance, the score of BNP PAM improves from 48% in 2019 to 99% in 2022. For Northern Trust AM, we have 21% in 2019 vs. 83% in 2022. If we consider the four largest US asset managers, they have improved their score between 2019 and 2021, but they backed fewer resolutions in 2022 than they did in 2021. This is certainly explained by the political pressure and the anti-ESG movement in the US\footnote{See Footnote 62 on page 29}. If we extend the analysis to 84 asset managers of the database, we obtain the dynamics given in Figure 6.10. Overall, trends are upward even if we notice some setbacks, especially in the US.

According to ShareAction (2023), the main findings are the following:

1. “49 additional resolutions would have received majority support if the largest asset managers had voted in favour of them.

2. Voting performance has been stagnant in the US and the UK compared to 2021, while European asset managers have shown a large improvement.
3. Asset managers across the board are hesitant to back action-oriented resolutions, which would have the most transformative impact on environmental and social issues.7

Other interesting results can be found in the four reports. For instance, we learn that only six asset managers filed or co-filed a shareholder resolution at any companies assessed in 2021 (ShareAction, 2021). In fact, it seems that most shareholder resolutions are filed by civil society organizations, small impact-focused asset managers, local governmental pension funds, and charitable or faith-based investors. For a comprehensive list of resolutions, the reader may consult the Insightia database (www.insightia.com), the Climate Action 100+ flagged shareholder votes (www.climateaction100.org), the Say on Climate resolutions (www.sayonclimate.org) or the proxy resolutions & voting guide of Interfaith Center on Corporate Responsibility (www.iccr.org).

Remark 47 In addition to the previous analysis, the 2022 ShareAction report includes statistics on say on climate resolutions. In this case, shareholders express approval or disapproval of the company’s global climate strategy. Among the 36 selected resolutions, only six were filed by shareholders, requesting the company to adopt an annual advisory vote on the company’s climate plan. The remaining thirty resolutions were management-sponsored standing votes requesting shareholders to approve the company’s climate plan. The shareholder- and management-sponsored votes received respectively 21.98% and 89.17% support on average.30 In Figure 6.11, we report the distribution of the support rate. We clearly see a big difference between shareholder- and management-sponsored votes.

Figure 6.11: Ranking of the 36 say on climate resolutions with respect to the support rate in %

Source: ShareAction (2023) & Author’s calculations.

30The range is between 1% and 46.5% for shareholder-sponsored resolutions, whereas it is between 51% and 99.9% for shareholder-sponsored resolutions.
Box 6.3: Case studies: Barclays, EDF and Woodside Energy say on climate resolutions

Electricité de France or EDF (French energy company) filed a management-sponsored say on climate resolution at its AGM on 12 May. The group’s climate transition plan to achieve carbon neutrality by 2050 was approved by 99.1%.

The management of Barclays (British bank) filed a say on climate resolution at the 2022 AGM on 4 May. They asked to approve the climate strategy, targets and progress of Barclays. Despite the plan’s insufficiencies regarding coal, the result was 80.8% for and 19.2% against. In certain special situations, some asset managers prefer to vote for with the hope that the company will improve its plan and return with an improved say on climate resolution next year. It seems that it was the case for Barclays according to some NGOs.

Woodside Energy Group Ltd. (Australian energy company) filed a say on climate resolution at its 2022 AGM on 19 May. The management asked to approve their climate report. The support rate was 51.03%, meaning that 48.97% of the company’s shareholders voted against its climate transition plan. These disappointed results may force the management to propose a new resolution in 2023 with a high risk of failure. Therefore, these results may also stop any new say on climate resolution filed by the management for the coming years.

Asset owners
Chapter 7

Extra-financial Accounting

7.1 Historical perspectives

7.2 Single vs. double materiality

7.3 Environmental accounting

7.3.1 National environmental accounts

7.3.2 Corporate environmental accounts

7.4 Sustainability accounting

7.4.1 Social issues

7.4.2 Governance factors