Asset Management
Lecture 4. Green and Sustainable Finance, ESG Investing and Climate Risk

Thierry Roncalli*

*University of Paris-Saclay

January 2021

General information

1. **Overview**
The objective of this course is to understand the theoretical and practical aspects of asset management
2. **Prerequisites**
M1 Finance or equivalent
3. **ECTS**
3
4. **Keywords**
Finance, Asset Management, Optimization, Statistics
5. **Hours**
Lectures: 24h, HomeWork: 30h
6. **Evaluation**
Project + oral examination
7. **Course website**
`http://www.thierry-roncalli.com/RiskBasedAM.html`

Objective of the course

The objective of the course is twofold:

1. having a financial culture on asset management
2. being proficient in quantitative portfolio management

Class schedule

Course sessions

- January 8 (6 hours, AM+PM)
- January 15 (6 hours, AM+PM)
- January 22 (6 hours, AM+PM)
- January 29 (6 hours, AM+PM)

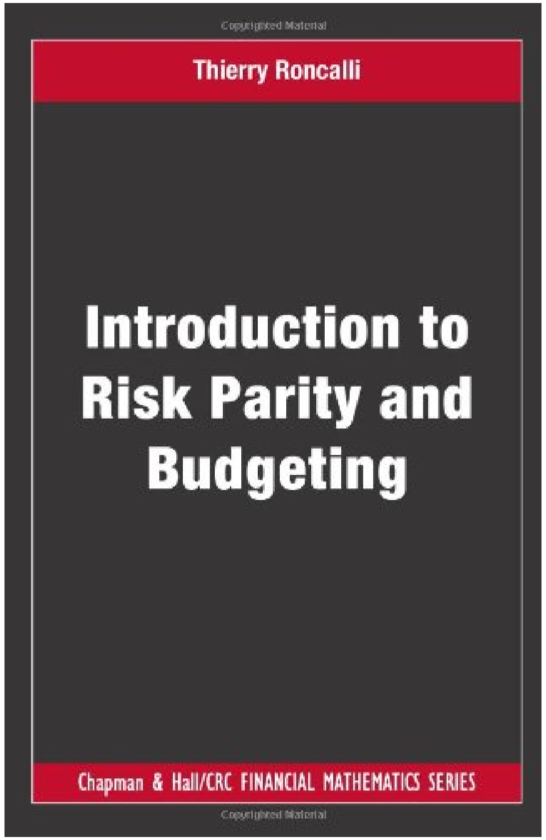
Class times: Fridays 9:00am-12:00pm, 1:00pm–4:00pm, University of Evry

Agenda

- Lecture 1: Portfolio Optimization
- Lecture 2: Risk Budgeting
- Lecture 3: Smart Beta, Factor Investing and Alternative Risk Premia
- Lecture 4: Green and Sustainable Finance, ESG Investing and Climate Risk
- Lecture 5: Machine Learning in Asset Management

Textbook

- Roncalli, T. (2013), *Introduction to Risk Parity and Budgeting*, Chapman & Hall/CRC Financial Mathematics Series.



Additional materials

- Slides, tutorial exercises and past exams can be downloaded at the following address:

  `http://www.thierry-roncalli.com/RiskBasedAM.html`

- Solutions of exercises can be found in the companion book, which can be downloaded at the following address:

  `http://www.thierry-roncalli.com/RiskParityBook.html`

Agenda

- Lecture 1: Portfolio Optimization
- Lecture 2: Risk Budgeting
- Lecture 3: Smart Beta, Factor Investing and Alternative Risk Premia
- **Lecture 4: Green and Sustainable Finance, ESG Investing and Climate Risk**
- Lecture 5: Machine Learning in Asset Management

Introduction to sustainable finance

Sustainable investing

Sustainable investing is an investment approach that considers environmental, social and governance (ESG) factors in portfolio selection and management

Socially responsible investing (SRI)

Socially responsible investing (SRI) is an investment strategy that is considered socially responsible, because it invests in companies that have ethical practices

Environmental, Social and Governance (ESG)

Environmental, Social, and Corporate Governance (ESG) refers to the factors that measure the sustainability of an investment

Introduction to sustainable finance

Sustainable Investing

$\approx$

Socially Responsible Investing (SRI)

$\approx$

Environmental, Social, and Governance (ESG)

Introduction to sustainable finance

Figure 1: The raison d'être of ESG investing

Introduction to sustainable finance

ESG financial ecosystem

- Asset owners (pension funds, sovereign wealth funds (SWF), insurance and institutional investors, retail investors, etc.)
- Asset managers
- ESG rating agencies
- ESG index sponsors
- Banks
- ESG associations (GSIA, UNPRI, etc.)
- Regulators and international bodies (governments, financial and industry regulators, central banks, etc.)
- **Issuers** (equities, bonds, loans, etc.)

ESG investing $\Leftrightarrow$ ESG financing

ESG regulations

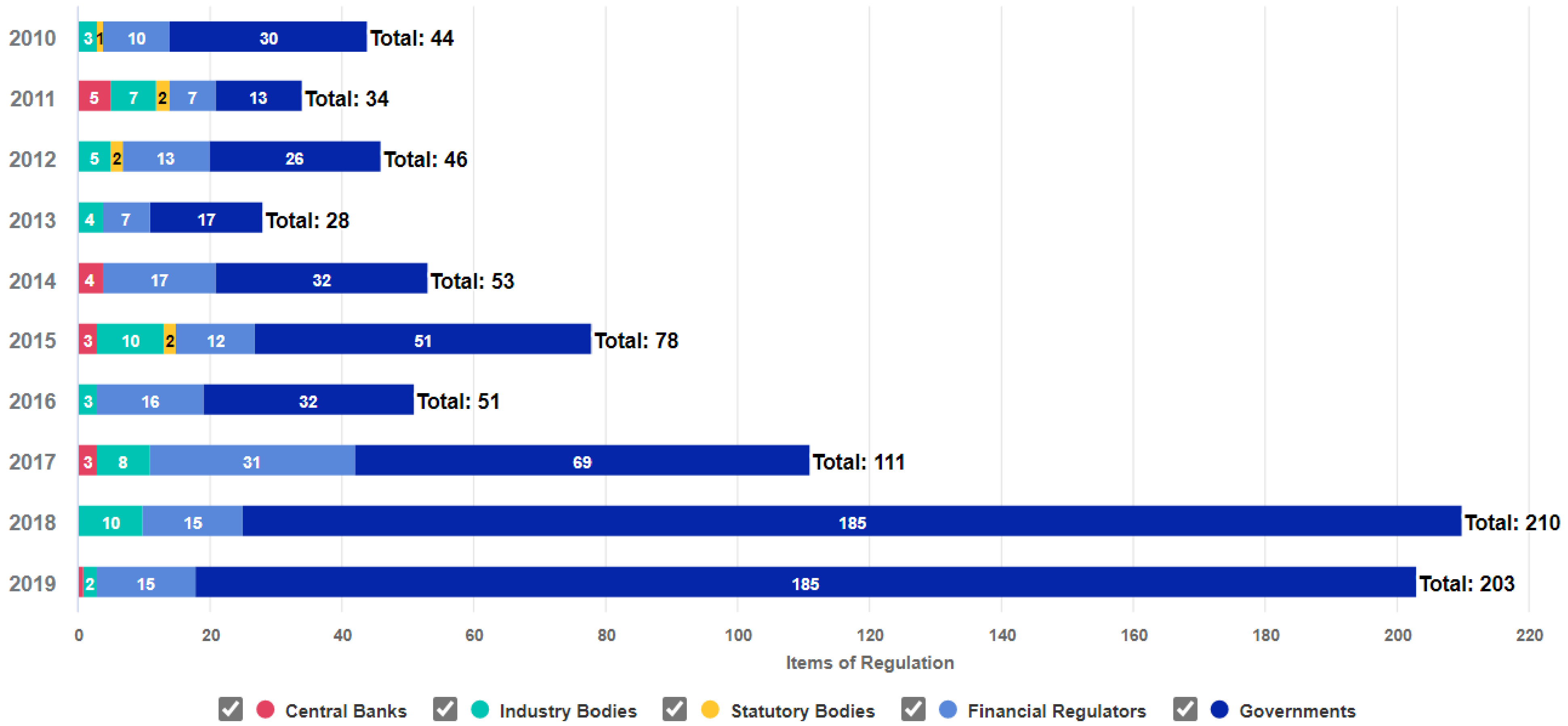


Figure 2: List of ESG regulations (MSCI, Who will regulate ESG?)

ESG regulations

Visit the MSCI website

`https://www.msci.com/who-will-regulate-esg`

and obtain the detailed list of regulations

by year, country, regulator, regulated investors, etc.

ESG regulators

The example of ESMA

ESMA strategy on sustainable finance

1. Completing the regulatory framework on transparency obligations via the Disclosures Regulation (joint technical standards with EBA and EIOPA)
2. TRV (trends, risks and vulnerabilities) reporting of sustainable finance
3. Analyse financial risks from climate change, including potentially climate-related stress testing
4. Convergence of national supervisory practices on ESG factors
5. Participating in the EU taxonomy on sustainable finance
6. Ensuring ESG guidelines are implemented by regulated entities (e.g. asset managers)

ESG regulators

The example of central banks

Figure 3: Network of Central Banks and Supervisors for Greening the Financial System (NGFS)

Go the NGFS website (`https://www.ngfs.net`) and download the NGFS climate scenarios

ESG associations

Figure 4: Global Sustainable Investment Alliance (GSIA)

`http://www.gsi-alliance.org`

ESG associations

GSIA members

- The European Sustainable Investment Forum (Eurosif), `http://www.eurosif.org`
- Responsible Investment Association Australasia (RIAA), `https://responsibleinvestment.org`
- Responsible Investment Association Canada (RIA Canada), `https://www.riacanada.ca`
- UK Sustainable Investment & Finance Association (UKSIF), `https://www.uksif.org`
- The Forum for Sustainable & Responsible Investment (US SIF), `https://www.ussif.org`
- Dutch Association of Investors for Sustainable Development (VBDO), `https://www.vbdo.nl/en/`
- Japan Sustainable Investment Forum (JSIF), `https://japansif.com/english`

ESG associations

Figure 5: Principles for Responsible Investment (PRI)

https://www.unpri.org

ESG associations

PRI (or UNPRI)

- Early 2005: 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
- April 2006: The Principles were launched at the New York Stock Exchange
- 6 ESG principles

ESG associations

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`

ESG associations

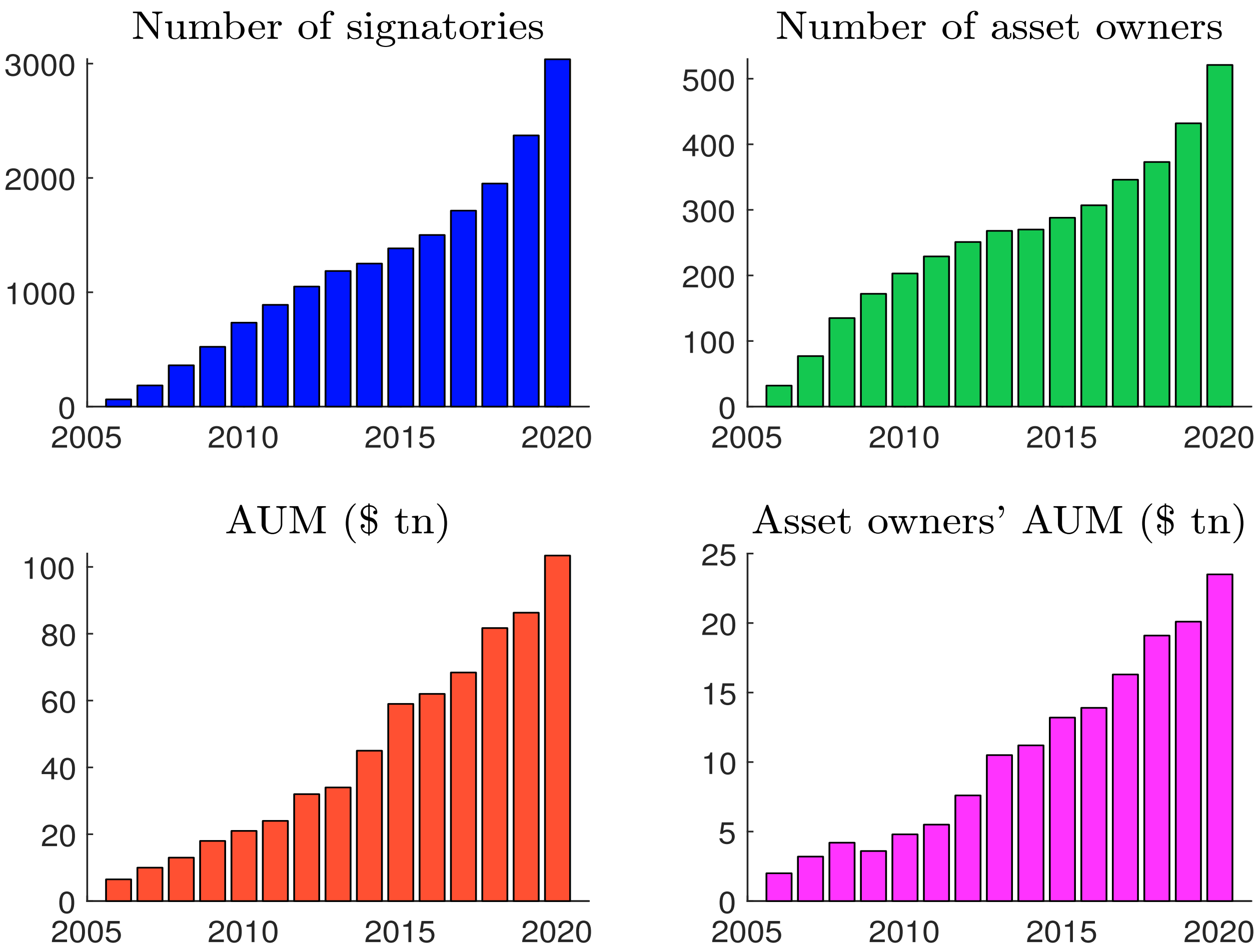


Figure 6: PRI Signatory growth

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

The issuer point of view of ESG

Corporate financial performance (CFP)

- Friedman (2007)
- Shareholder theory
- Corporations have no social responsibility to the public or society
- Their only responsibility is to its shareholders (profit maximization)

Corporate social responsibility (CSR)

- Freeman (2010)
- Stakeholder theory
- Corporations create negative externalities
- They must have social and moral responsibilities
- Impact on the cost-of-capital and business risk

ESG strategies

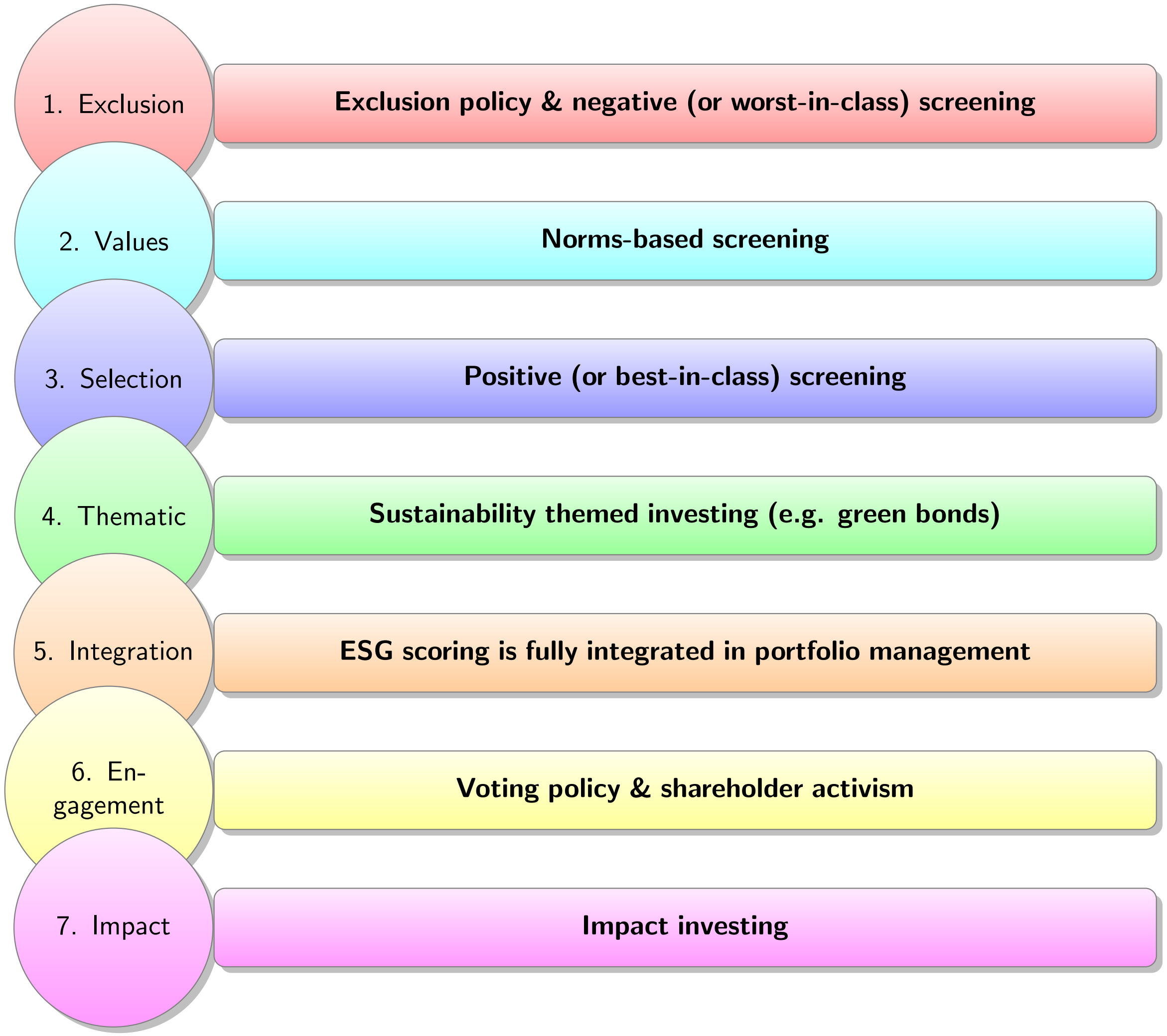


Figure 7: Categorisation of ESG strategies (Eurosif, 2019)

ESG strategies

Exclusion/Negative Screening

The exclusion from a fund or portfolio of certain sectors, companies or practices based on specific ESG criteria (worst-in-class)

Values/Norms-based Screening (or Red Flags)

Screening of investments against minimum standards of business practice based on international norms, such as those issued by the OECD, ILO, UN and UNICEF[a]

[a] In Europe, the top exclusion criteria 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, 2019)

Source: Global Sustainable Investment Alliance (2018)

ESG strategies

Selection/Positive Screening

Investment in sectors, companies or projects selected for positive ESG performance relative to industry peers (best-in-class)

Thematic/Sustainability Themed Investing

Investment in themes or assets specifically related to sustainability (for example clean energy, green technology or sustainable agriculture)

ESG Integration

The systematic and explicit inclusion by investment managers of environmental, social and governance factors into financial analysis

Source: Global Sustainable Investment Alliance (2018)

ESG strategies

Engagement/Shareholder Action

The use of shareholder power 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 comprehensive ESG guidelines.

Impact Investing

Targeted investments aimed at solving social or environmental problems, and including community investing, where capital is specifically directed to traditionally underserved individuals or communities, as well as financing that is provided to businesses with a clear social or environmental purpose

Source: Global Sustainable Investment Alliance (2018)

The market of ESG investing

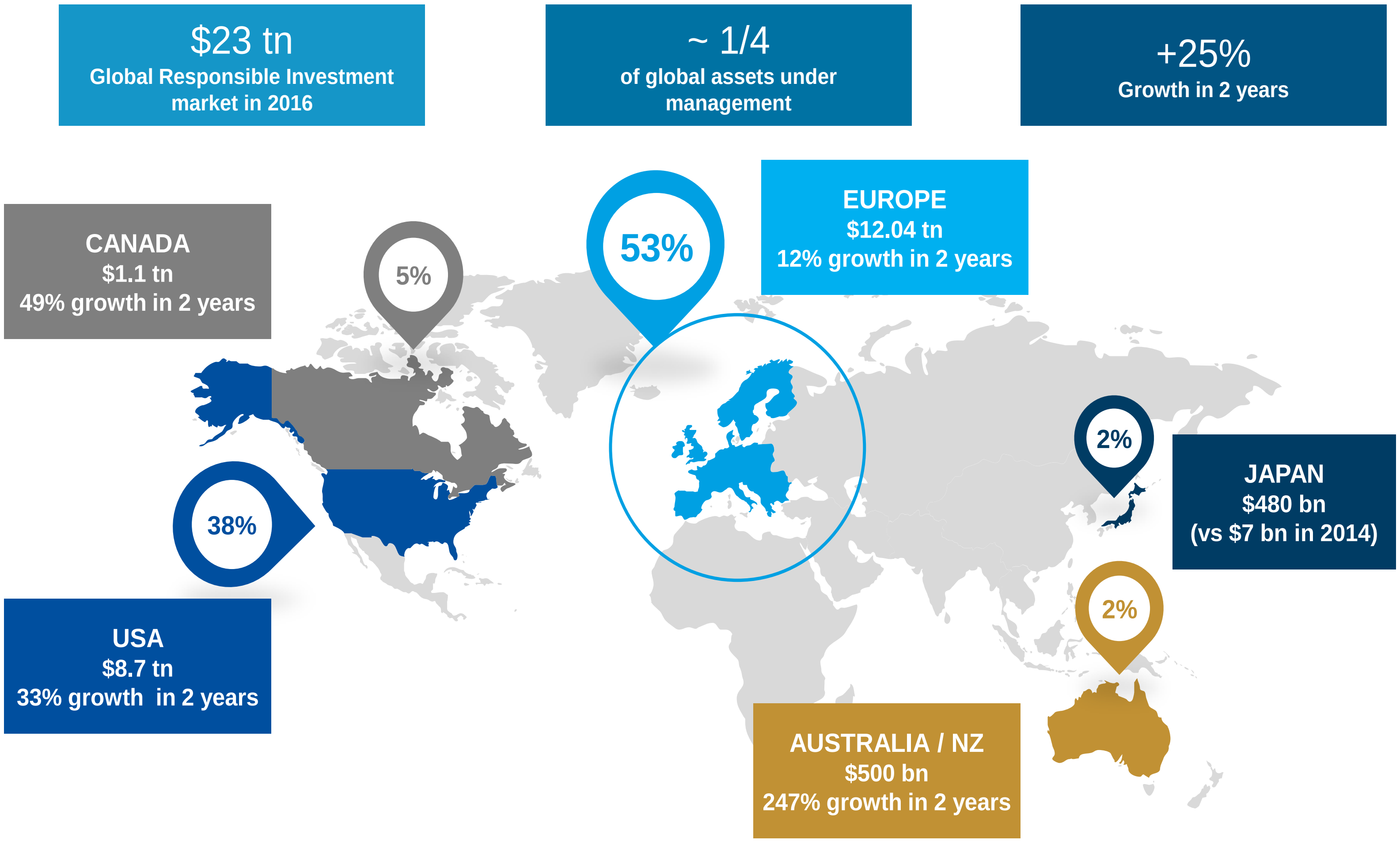


Figure 8: ESG at the start of 2016

Source: Global Sustainable Investment Alliance (2017)

The market of ESG investing

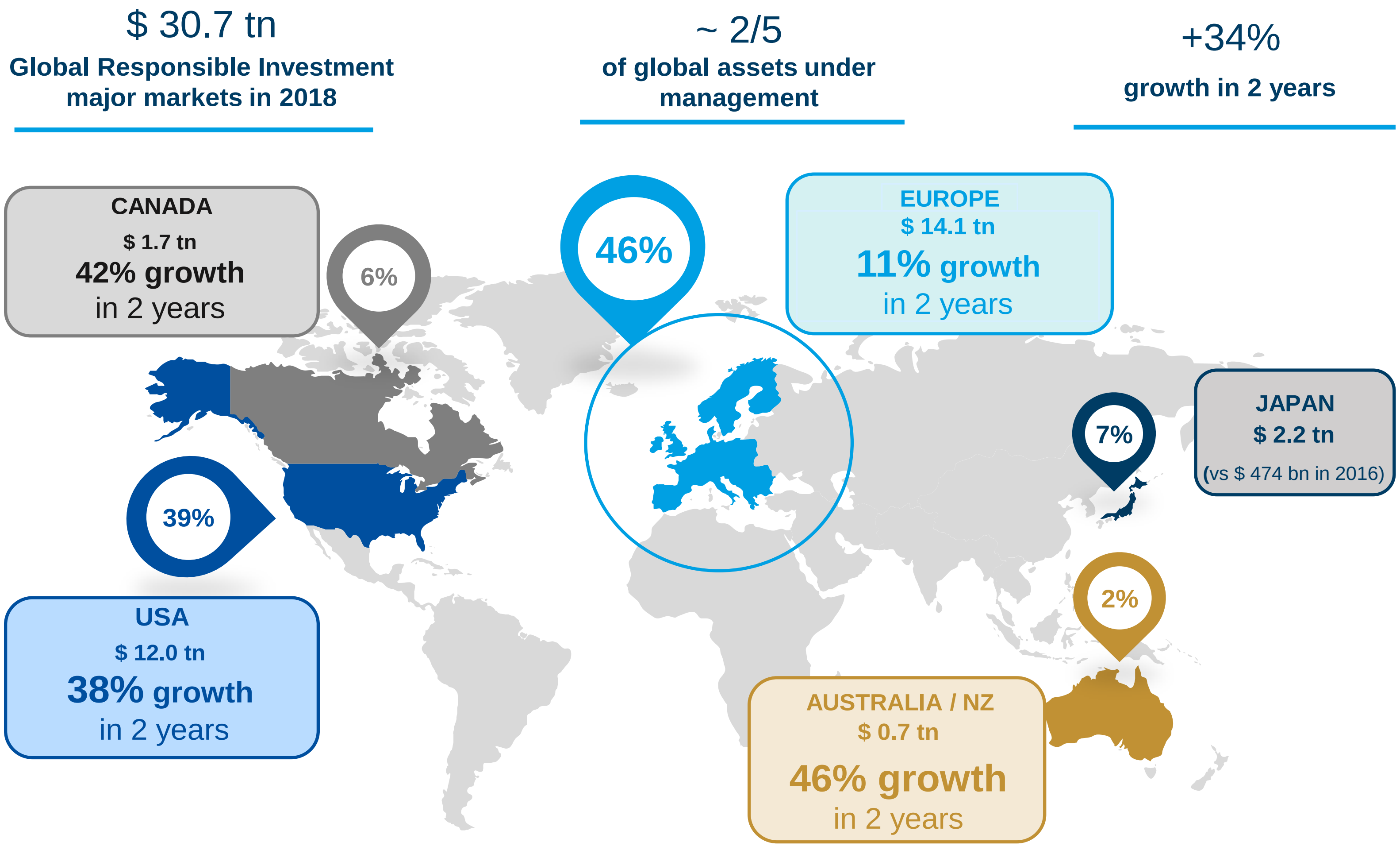


Figure 9: ESG at the start of 2018

Source: Global Sustainable Investment Alliance (2019)

The market of ESG investing

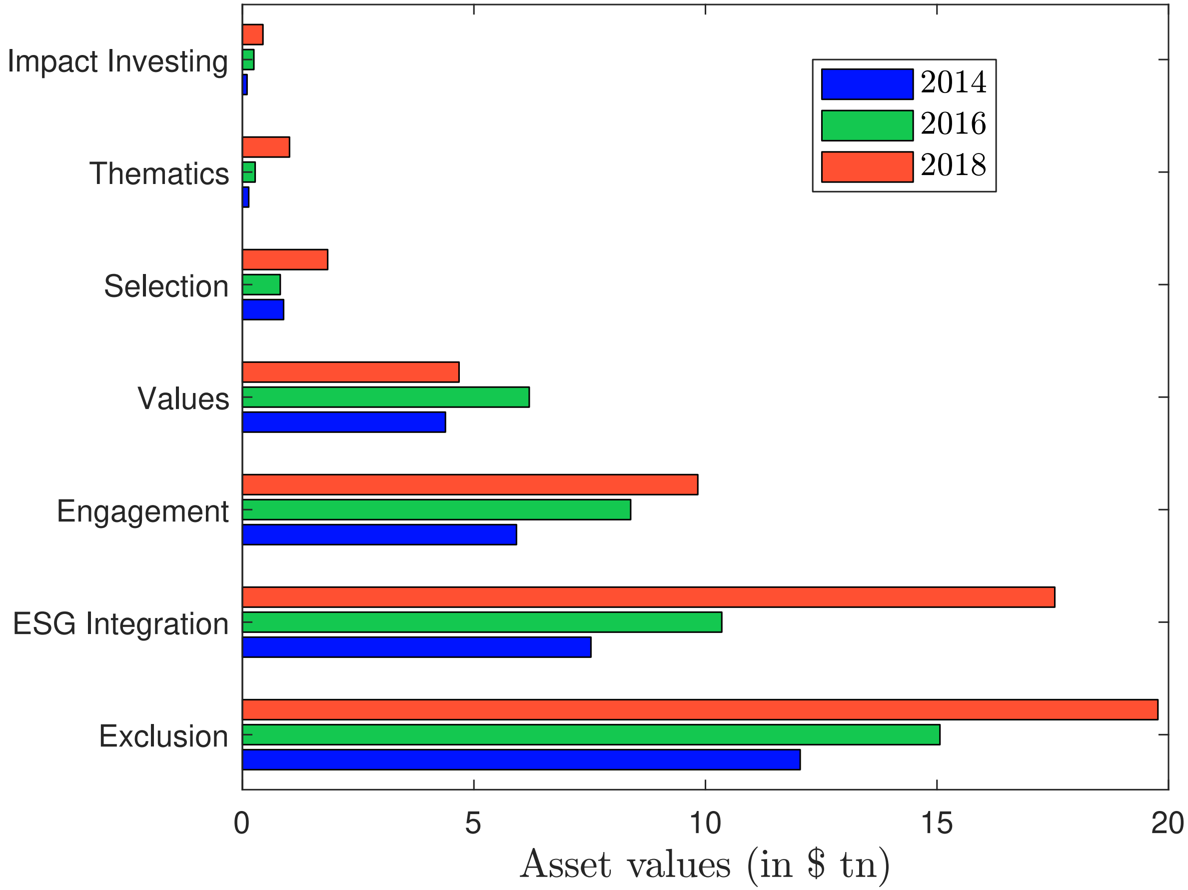


Figure 10: Asset values of ESG strategies between 2014 and 2018

Source: Global Sustainable Investment Alliance (2015, 2017, 2019)

The market of ESG investing

Table 1: Annual growth of ESG strategies

	2014-2016	2016-2018
Exclusion	11.7%	14.6%
ESG Integration	17.4%	30.2%
Engagement	18.9%	8.3%
Values	19.0%	−13.1%
Selection	7.6%	50.1%
Thematics	55.1%	92.0%
Impact Investing	56.8%	33.7%

Source: Global Sustainable Investment Alliance (2015, 2017, 2019)

The concept of ESG investing

Environmental, **S**ocial and **G**overnance (ESG)

- ESG **analysis**: extra-financial analysis $\neq$ financial analysis
- ESG **scoring**: quantitative measures of ESG dimensions
- ESG **ratings**: provide a grade (e.g. AAA, AA, A, etc.) to an issuer ($\approx$ credit ratings)
- ESG **screening**: process of scanning and filtering issuers based on ESG analysis and scoring ($\approx$ stock screening, bond screening, stock picking)
- ESG **investment process**: define how the investment process integrates ESG
- ESG **reporting**: provide ESG information and measures on the investment portfolio (e.g. ESG risk of the portfolio vs ESG risk of the benchmark, repartition of ESG ratings, top/bottom ESG issuers, etc.)

ESG rating agencies

Major players

- ISS ESG (Deutsche Börse)
- MSCI ESG
- Sustainalytics (Morningstar)
- Thomson Reuters
- Vigeo-Eiris (Moody's)

Other players

- Beyond Ratings (LSE)
- Bloomberg ESG
- RobecoSAM (S&P)
- Refinitiv (LSE)
- TrueValue Labs (Factset)

Specialized climate data providers

- CDP
- Trucost (S&P)

ESG data

- ESG requires a lot of data and **alternative** data
- For example, Sustainalytics ESG Data includes 220 ESG indicators and 450 fields, and covers over 12 000 companies
- Where to find the data?
  - Public data
    - Standardized data (regulatory reporting)
    - Non-standardized data (self reporting)
  - Private data
  - Proprietary data
  - Questionnaire/survey
  - Analyst scores

ESG data

Examples of data

- Corporate annual reports
- Corporate environmental and social reports
- Carbon Disclosure Project (CDP) responses
- US Bureau of Labor Statistics
- Thomson Financial
- World Bank (WB)

ESG data

Examples of alternative data

- Energy Data Analytics Lab research (Duke university)
  https://energy.duke.edu/research/energy-data/resources
- Food and Agriculture Organization (FAO)
  http://www.fao.org
- UK Reporting of Injuries, Diseases and Dangerous Occurrences Regulations (RIDDOR)
  https://www.hse.gov.uk/riddor
- World Health Organization (WHO)
  https://www.who.int
- World Bank Governance Indicators (WGI)
  https://info.worldbank.org/governance/wgi
- World Resources Institute (WRI)
  https://www.wri.org

ESG (alternative) data

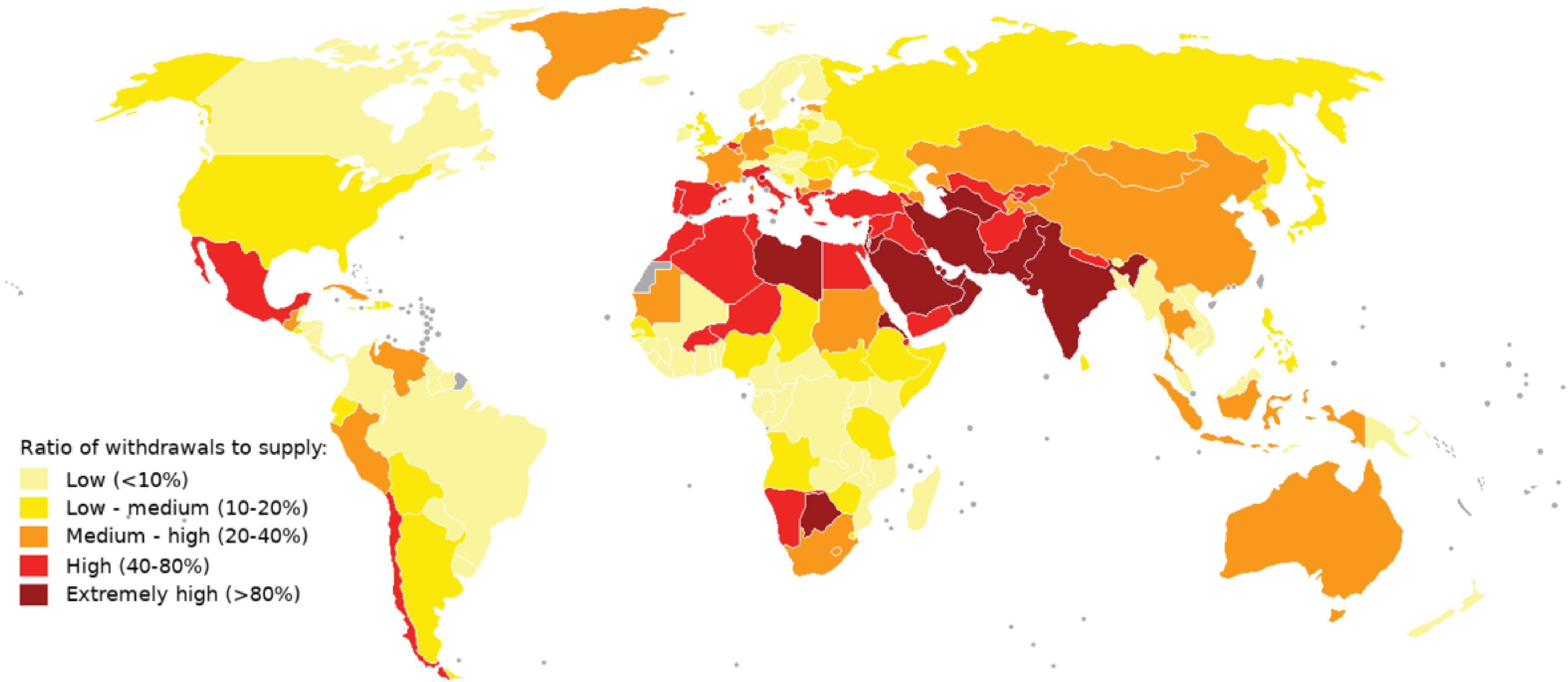


Figure 11: WRI Water Stress 2019

Source: World Resources Institute (WRI), www.wri.org

ESG (alternative) data

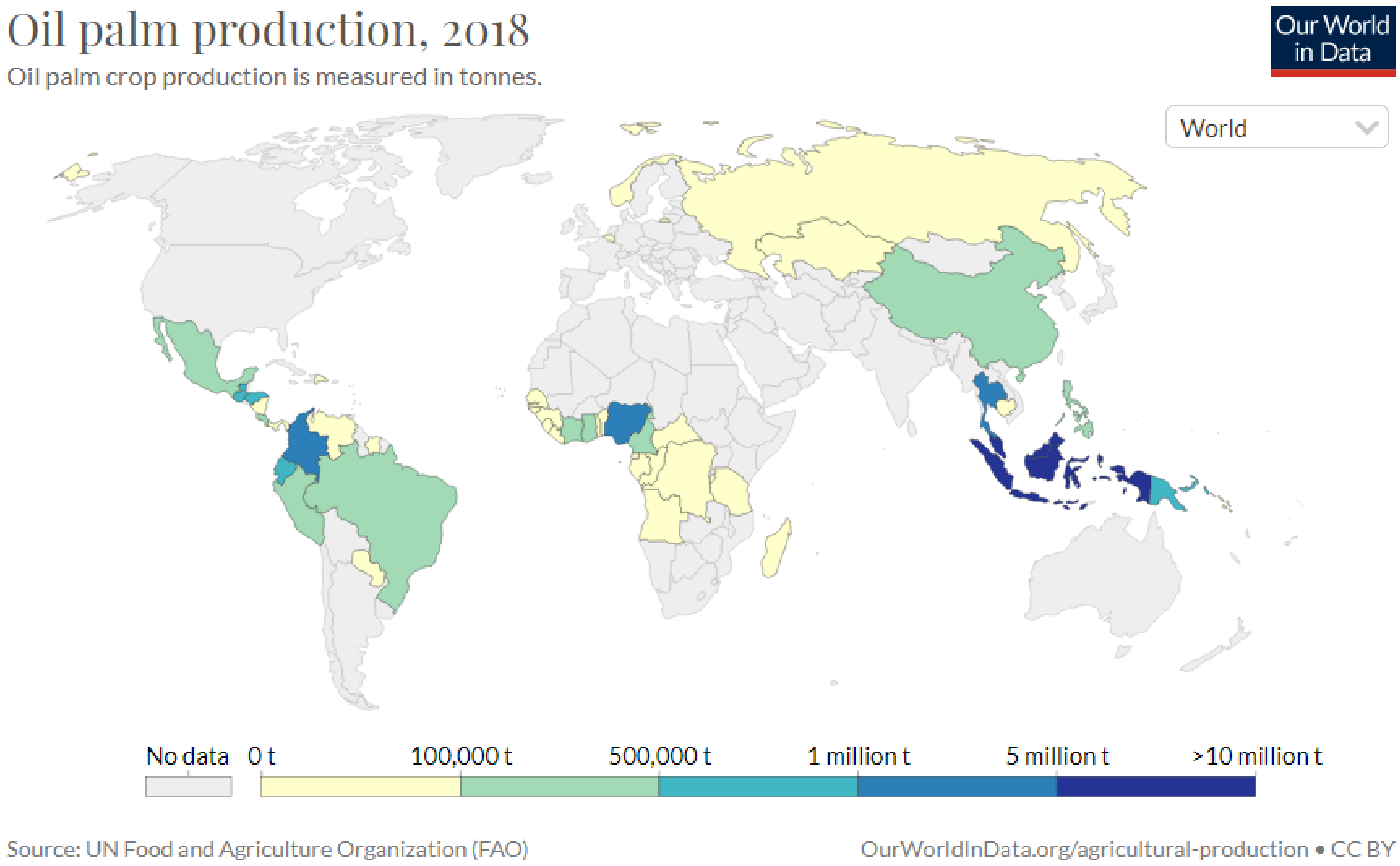


Figure 12: Oil palm production in 2018

Source: Our World in Data, `https://ourworldindata.org/grapher/palm-oil-production`

ESG (alternative) data

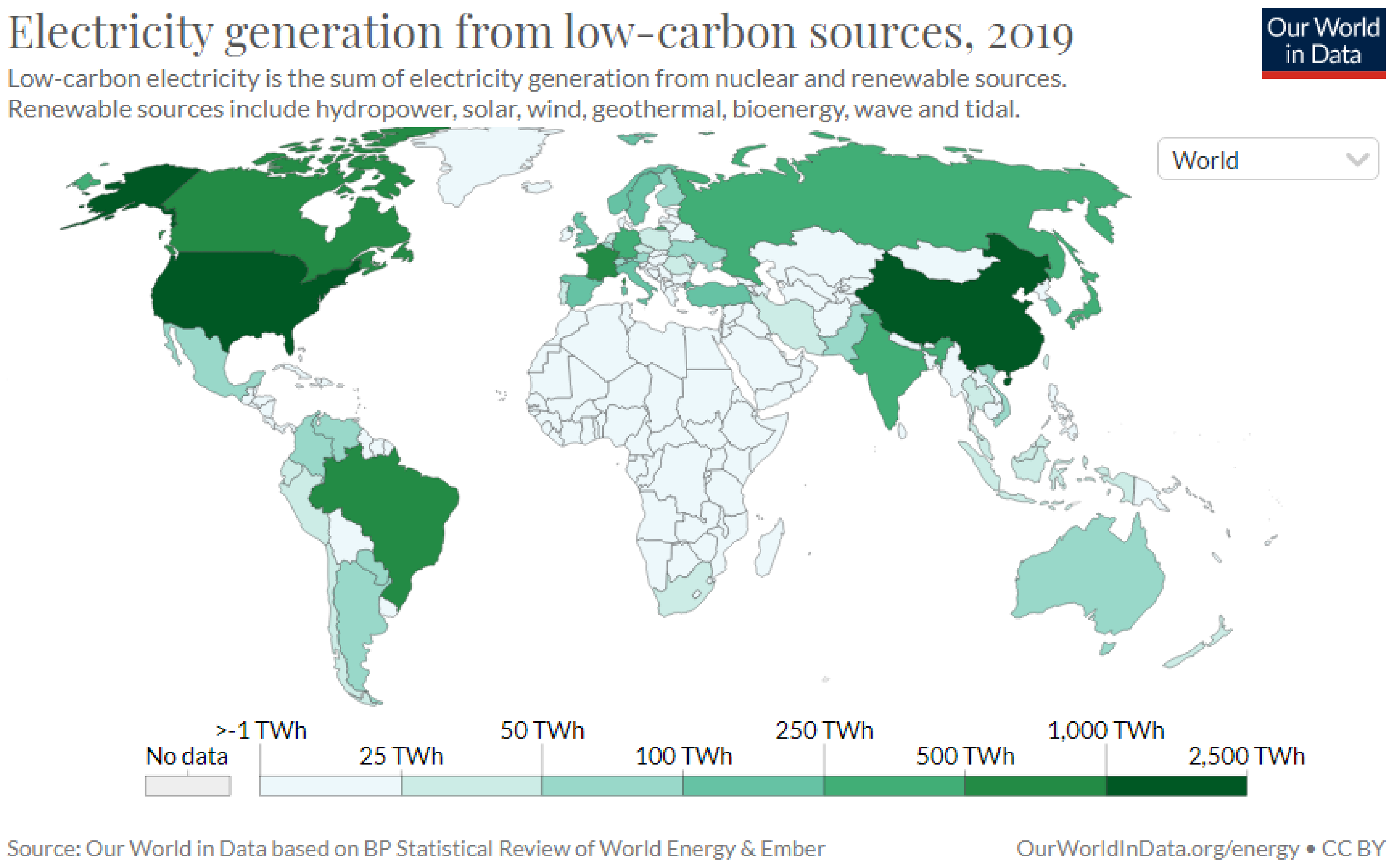


Figure 13: Electricity generation from low-carbon sources in 2019

Source: Our World in Data, `https://ourworldindata.org/grapher/low-carbon-electricity`

ESG scoring system

Table 2: An example of ESG criteria (corporate issuers)

Environmental	Social	Governance
Carbon emissions	Employment conditions	Board independence
Energy use	Community involvement	Corporate behaviour
Pollution	Gender equality	Audit and control
Waste disposal	Diversity	Executive compensation
Water use	Stakeholder opposition	Shareholder' rights
Renewable energy	Access to medicine	CSR strategy
Green cars*		
Green financing*		

$^{(\star)}$means a specific criterion related to one or several sectors (Green cars $\Rightarrow$ Automobiles, Green financing $\Rightarrow$ Financials)

ESG scoring system

Table 3: An example of ESG criteria (sovereign issuers)

Environmental

- Carbon emissions
- Energy transition risk
- Fossil fuel exposure
- Emissions reduction target
- Physical risk exposure
- Green economy

Social

- Income inequality
- Living standards
- Non-discrimination
- Health & security
- Local communities and human rights
- Social cohesion
- Access to education

Governance

- Political stability
- Institutional strength
- Levels of corruption
- Rule of law
- Government and regulatory effectiveness
- Rights of shareholders

ESG scoring system

Sovereign ESG Data Framework

- World Bank
- Data may be download at the following webpage:
  `https://datatopics.worldbank.org/esg/framework.html`
- E: 27 variables
- S: 22 variables
- G: 18 variables

ESG scoring system

Table 4: Sovereign ESG Data Framework (World Bank)

Environmental

- Emissions & pollution (5)
- Natural capital endowment and management (6)
- Energy use & security (7)
- Environment/ climate risk & resilience (6)
- Food security (3)

Social

- Education & skills (3)
- Employment (3)
- Demography (3)
- Poverty & inequality (4)
- Health & nutrition (5)
- Access to services (4)

Governance

- Human rights (2)
- Government effectiveness (2)
- Stability & rule of law (4)
- Economic environment (3)
- Gender (4)
- Innovation (3)

ESG scoring system

- Most of ESG scoring systems are based on scoring trees
- Raw data are normalized in order to obtain features $X_1, \ldots, X_m$
- Features $X_1, \ldots, X_m$ are aggregated to obtain sub-scores $\mathcal{s}_1, \ldots, \mathcal{s}_n$:

$$\mathcal{s}_i = \sum_{j=1}^{m} \omega_{i,j}^{(1)} X_j$$

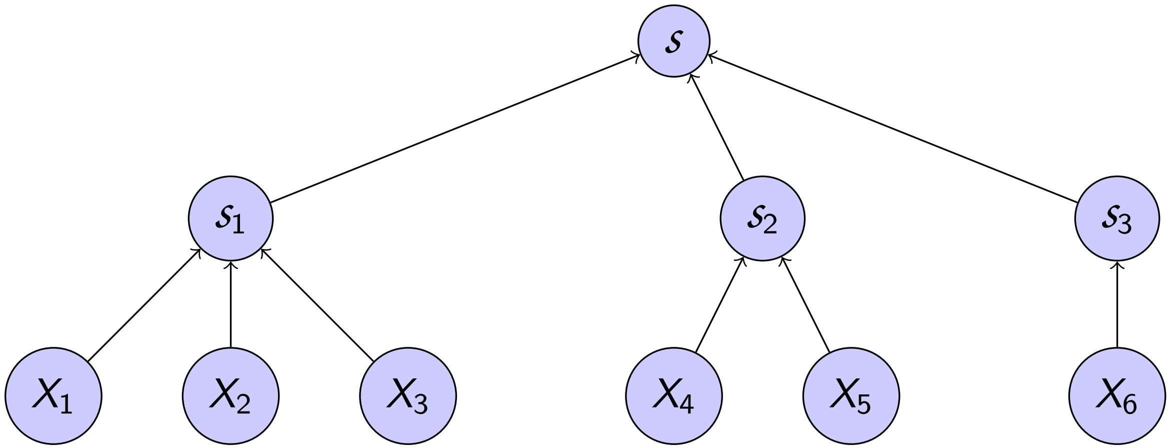
- Sub-scores $\mathcal{s}_1, \ldots, \mathcal{s}_n$ are aggregated to obtain the final score $\mathcal{s}$:

$$\mathcal{s} = \sum_{i=1}^{n} \omega_i^{(2)} \mathcal{s}_i$$

The two-level tree structure can be extended to multi-level tree structures
For example, in the case of a three-level tree structure, we have:

$$\text{Features} \Rightarrow \text{sub-sub-scores} \Rightarrow \text{sub-scores} \Rightarrow \text{final score}$$

ESG scoring system



We assume that:

- Level 1
  1. $\omega_{1,1}^{(1)} = 50\%$
     $\omega_{2,1}^{(1)} = 25\%$
     $\omega_{3,1}^{(1)} = 25\%$
  2. $\omega_{4,2}^{(1)} = 50\%$
     $\omega_{5,2}^{(1)} = 50\%$
  3. $\omega_{6,3}^{(1)} = 100\%$
- Level 2: $\omega_1^{(2)} = \omega_2^{(2)} = \omega_3^{(2)} = 33.33\%$

Figure 14: A two-level tree structure

ESG scoring system

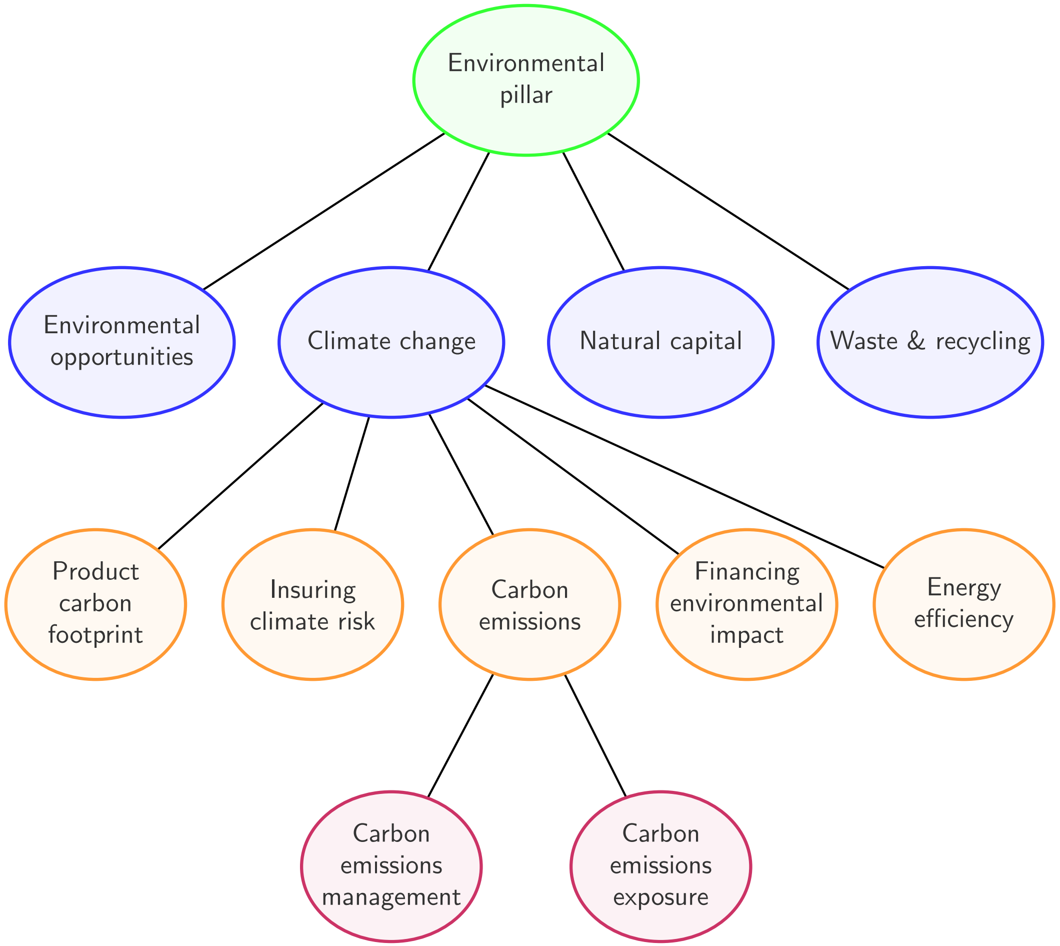


Figure 15: An example of ESG scoring tree (MSCI methodology)

Source: MSCI (2020)

ESG scoring system

Raw data and scores have to be normalized

Why? Because to facilitate the aggregation process

Several normalization approaches:

- $0-1$ normalization: $X_j \in [0,1] \Rightarrow s_i \in [0,1]$
- $0-100$ normalization: $X_j \in [0,100] \Rightarrow s_i \in [0,100]$
- z-score normalisation:

$$z_{i,j} = \frac{X_{i,j} - \hat{\mu}(X_j)}{\hat{\sigma}(X_j)}$$

- Empirical normalization using the empirical probability distribution ($0-1$ normalization)

ESG scoring system

Table 5: Computation of z-score

Observation	X_1	z_1	X_2	z_2
1	70.4000	−0.0015	0.0340	0.6911
2	31.3000	−1.0089	0.1000	1.3918
3	66.0000	−0.1149	−0.1660	−1.4321
4	84.2000	0.3540	−0.0590	−0.2962
5	91.7000	0.5472	−0.0280	0.0329
6	53.4000	−0.4395	0.0420	0.7760
7	49.6000	−0.5375	−0.1670	−1.4427
8	133.4000	1.6216	0.0470	0.8291
9	5.1000	−1.6840	−0.1210	−0.9544
10	119.5000	1.2635	0.0070	0.4045
Mean	70.4600	0.0000	−0.0311	0.0000
Standard deviation	38.8127	1.0000	0.0942	1.0000

We have $z_{1,8} = \frac{133.4-70.46}{38.8127} = 1.6216$ and $z_{2,1} = \frac{0.0340-(0.0311)}{0.0942} = 0.6911$

ESG scoring system

Sector neutrality

- Most of ESG scoring systems are sector neutral
- The normalization is done at the sector level, not at the universe level
- ESG scores are then relative (with respect to a sector), not absolute
- Best-in-class/worst-in-class issuers $\neq$ best/worst issuers

ESG rating system

We need a mapping function $\mathcal{M}_{\mathrm{apping}}$ to transform the ESG score $\mathcal{S}$ into an ESG rating $\mathcal{R}$

MSCI methodology

$$\begin{array}{rrcl} \mathcal{M}_{\mathrm{apping}}: & [0,10] & \longrightarrow & \{\mathrm{AAA},\mathrm{AA},\mathrm{A},\mathrm{BBB},\mathrm{BB},\mathrm{B},\mathrm{CCC}\} \\ & \mathcal{S} & \longmapsto & \mathcal{R} = \mathcal{M}_{\mathrm{apping}}(\mathcal{S}) \end{array}$$

- If $\mathcal{S} \in \left[0, \frac{10}{7}\right]$, $\mathcal{M}_{\mathrm{apping}}(\mathcal{S}) = \mathrm{CCC}$
- If $\mathcal{S} \in \left[\frac{10}{7}, \frac{2\times 10}{7}\right]$, $\mathcal{M}_{\mathrm{apping}}(\mathcal{S}) = \mathrm{B}$
- If $\mathcal{S} \in \left[\frac{2\times 10}{7}, \frac{3\times 10}{7}\right]$, $\mathcal{M}_{\mathrm{apping}}(\mathcal{S}) = \mathrm{BB}$
- If $\mathcal{S} \in \left[\frac{3\times 10}{7}, \frac{4\times 10}{7}\right]$, $\mathcal{M}_{\mathrm{apping}}(\mathcal{S}) = \mathrm{BBB}$
- If $\mathcal{S} \in \left[\frac{4\times 10}{7}, \frac{5\times 10}{7}\right]$, $\mathcal{M}_{\mathrm{apping}}(\mathcal{S}) = \mathrm{A}$
- If $\mathcal{S} \in \left[\frac{5\times 10}{7}, \frac{6\times 10}{7}\right]$, $\mathcal{M}_{\mathrm{apping}}(\mathcal{S}) = \mathrm{AA}$
- If $\mathcal{S} \in \left[\frac{6\times 10}{7}, 10\right]$, $\mathcal{M}_{\mathrm{apping}}(\mathcal{S}) = \mathrm{AAA}$

ESG rating system

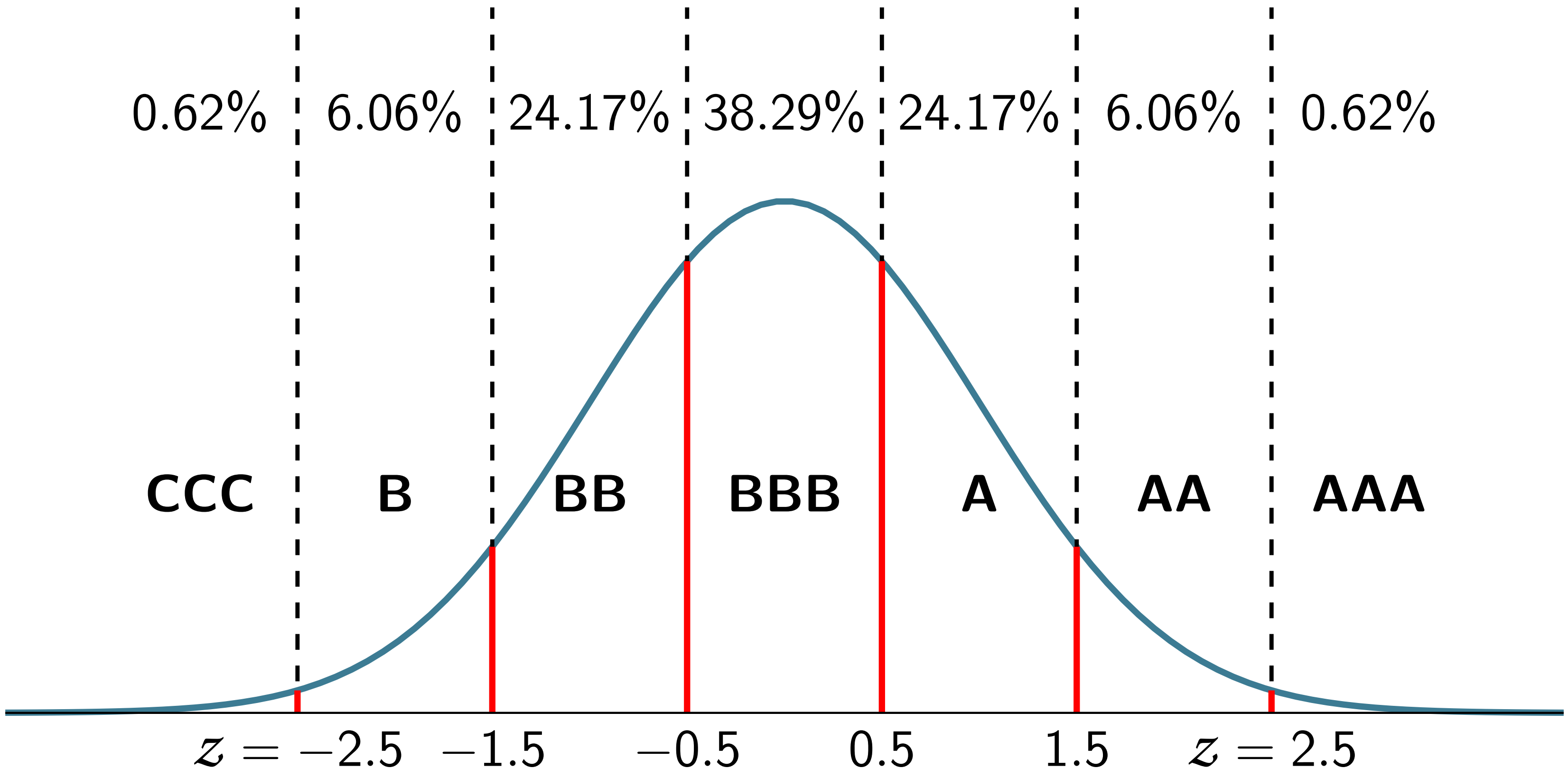


Figure 16: From ESG scores to ESG ratings (Gaussian mapping* of the z-score)

*We have $\Phi(-2.5) = 0.62\%$, $\Phi(-1.5) - \Phi(-2.5) = 6.06\%$, $\Phi(-0.5) - \Phi(-1.5) = 24.17\%$, $\Phi(0.5) - \Phi(-0.5) = 38.29\%$, $\Phi(1.5) - \Phi(0.5) = 24.17\%$, $\Phi(2.5) - \Phi(1.5) = 6.06\%$ and $1 - \Phi(2.5) = 0.62\%$

ESG ratings versus credit ratings

Credit rating

- What is the question?
  Measuring the 1Y PD
- Rating correlation $\geq 90\%$
  Convergence in the 1990s
- **Absolute** rating
  $\Rightarrow$ Facilitates comparison
- More stable
- Accounting standards

ESG rating

- What is the question?
  ???
- Rating correlation $\leq 40\%$
  European issuers $>$ American issuers $>$ Japanese issuers (≈ 0)
- **Relative** rating
  $\Rightarrow$ Complicates comparison
- Less stable
- ESG standardization and the issue of self-reporting

What can we anticipate? $\Rightarrow$ Strong convergence for subcomponents, (more or less) convergence for **E**, **S**, and **G** ratings, but not for **ESG** ratings

The example of Tesla!

What is the performance of ESG investing?

Impact on stock returns

- Stock financial performance $\neq$ corporate financial performance
- Heterogenous results
- Return-oriented or risk-oriented investment style?
- Mixed results

What is the performance of ESG investing?

Academic findings

- Relationship between shareholder rights and "*higher firm value, higher profits, higher sales growth, lower capital expenditures, and [...] fewer corporate acquisitions*" (Gompers *et al.*, 2003)
- Positive relation between high corporate social responsibility and low cost of equity capital (El Ghoul *et al.*, 2011): "*Employee Relations, Environmental Policies, Product Strategies lower the firms' cost of equity*"
- Corporate financial performance is a U-shape function of corporate social performance (Barnett and Salomon, 2012)
- Cultural differences explain the diversity and differences in intentions ('Value' or 'Values' oriented) of the currently available ESG data (Eccles and Stroehle, 2018)
- Negative/neutral impact: Schröder (2007), Hong and Kacperczyk (2009)

Mixed results

What is the performance of ESG investing?

We consider the two studies conducted by Amundi Quantitative Research:

- 2010-2017
  Bennani, L., Le Guenedal, T., Lepetit, F., Ly, L., Mortier, V., Roncalli, T., and Sekine T. (2018), How ESG Investing Has Impacted the Asset Pricing in the Equity Market, Amundi Discussion Paper, DP-39-2018, `https://research-center.amundi.com`
- 2018-2019
  Drei, A., Le Guenedal, T., Lepetit, F., Mortier, V., Roncalli, T., and Sekine T. (2020), ESG Investing in Recent Years: New Insights from Old Challenges, Amundi Discussion Paper, DP-42-2019, `https://research-center.amundi.com`

2010 – 2017: From hell to heaven

- ESG investing tended to penalize both passive and active ESG investors between 2010 and 2013
- Contrastingly, ESG investing was a source of outperformance from 2014 to 2017 in Europe and North America
- Two success stories between 2014 and 2017: **E**nvironmental in North America and **G**overnance in the Eurozone
- ESG was a risk factor (or a beta strategy) in the Eurozone, whereas it was an alpha strategy in North America

Active management

Sorted portfolio methodology

Sorted-portfolio approach

- Sorted-based approach of Fama-French (1992)
- At each rebalancing date t, we rank the stocks according to their Amundi **ESG** z-score $s_{i,t}$
- We form the five quintile portfolios Q_i for $i = 1, \ldots, 5$
- The portfolio Q_i is invested during the period $]t, t+1]$:
  - Q_1 corresponds to the best-in-class portfolio (best scores)
  - Q_5 corresponds to the worst-in-class portfolio (worst scores)
- Quarterly rebalancing
- Universe: MSCI World Index
- Equally-weighted and sector-neutral portfolio (and region-neutral for the world universe)

Performance of ESG active management (2010 – 2017)

North America

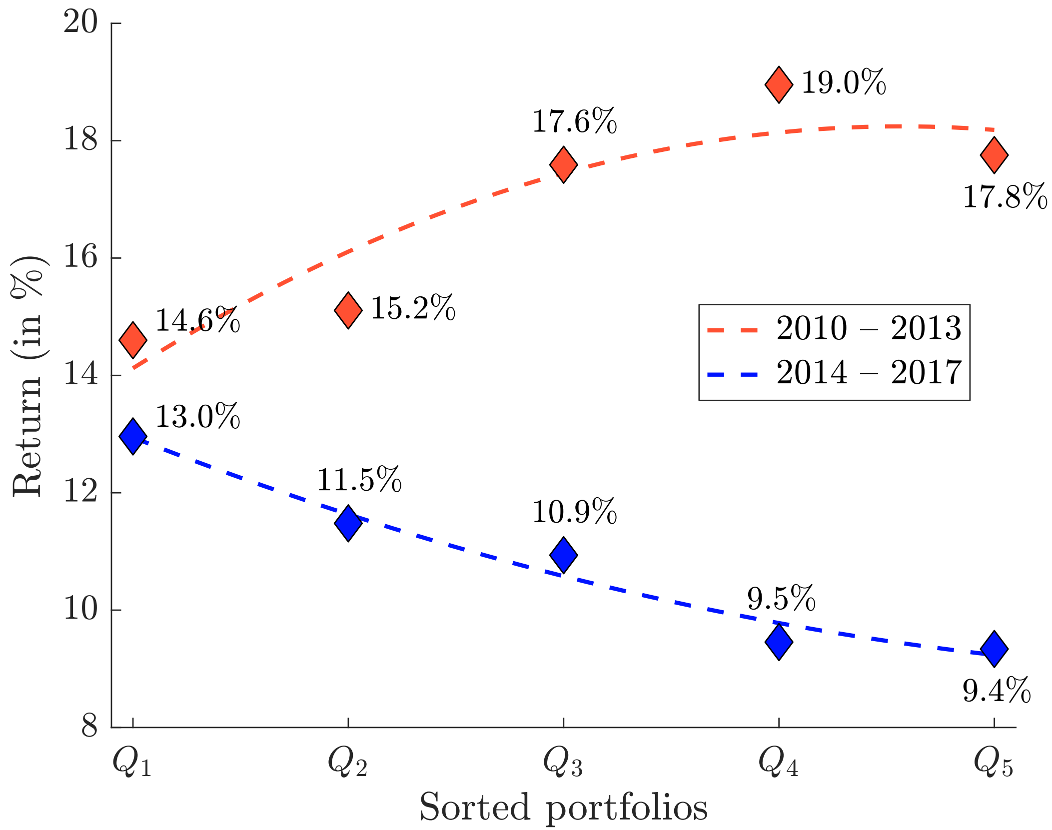


Figure 17: Annualized return of **ESG** sorted portfolios (North America)

Source: Amundi Quantitative Research (2018)

Performance of ESG active management (2010 – 2017)

Eurozone

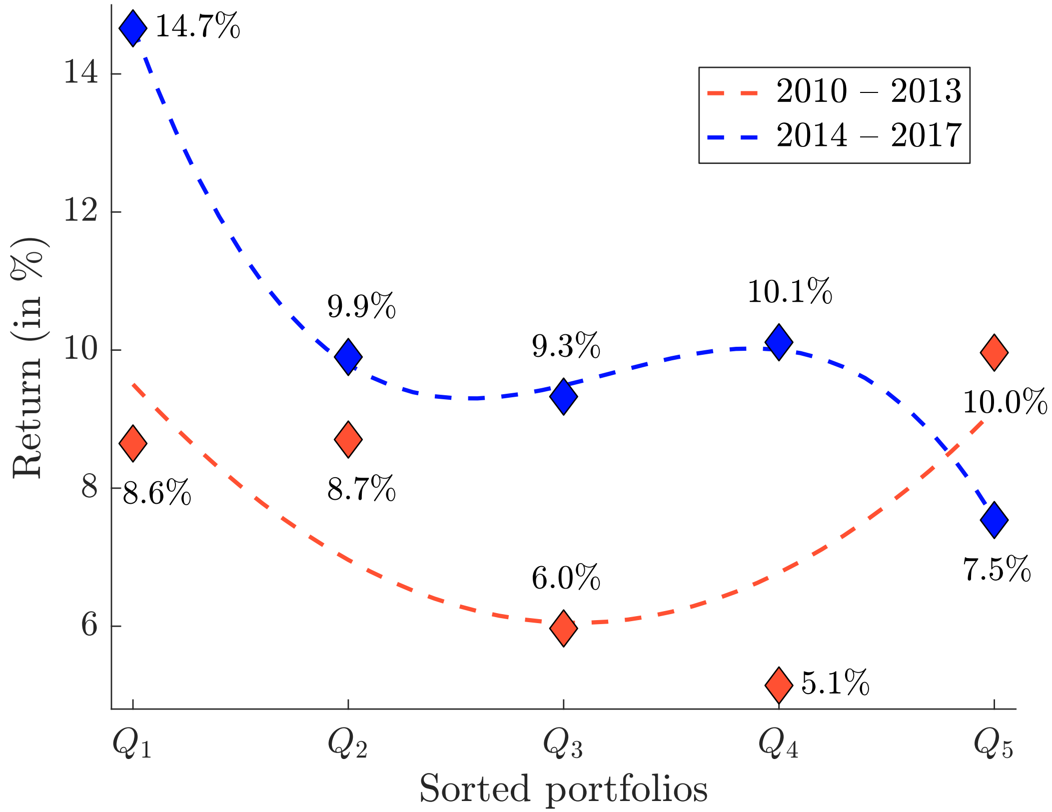


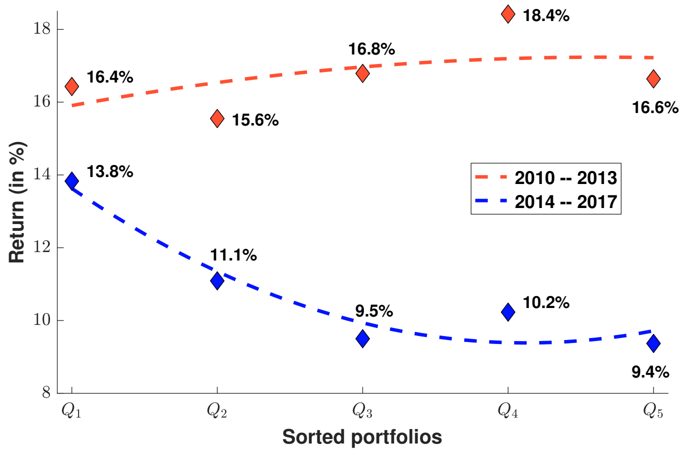
Figure 18: Annualized return of **ESG** sorted portfolios (Eurozone)

Source: Amundi Quantitative Research (2018)

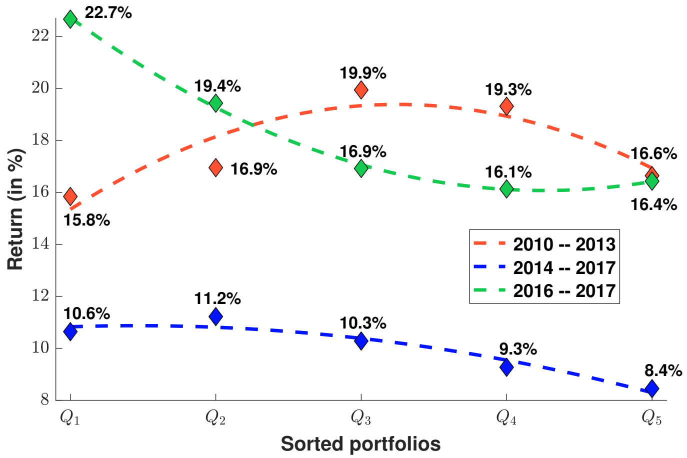
Performance of ESG active management (2010 – 2017)

North America

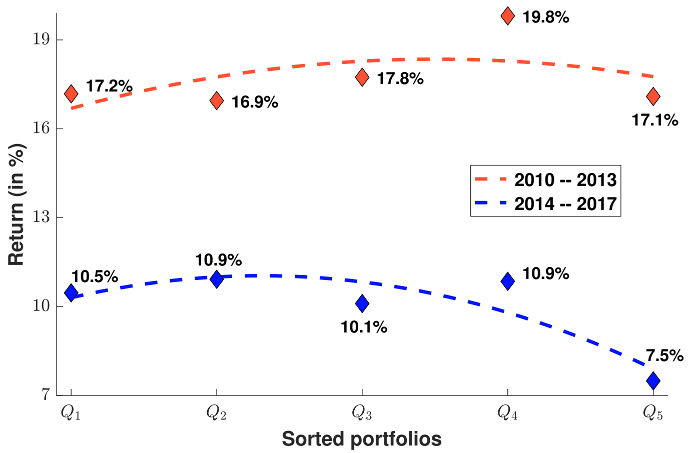
Environmental



Social



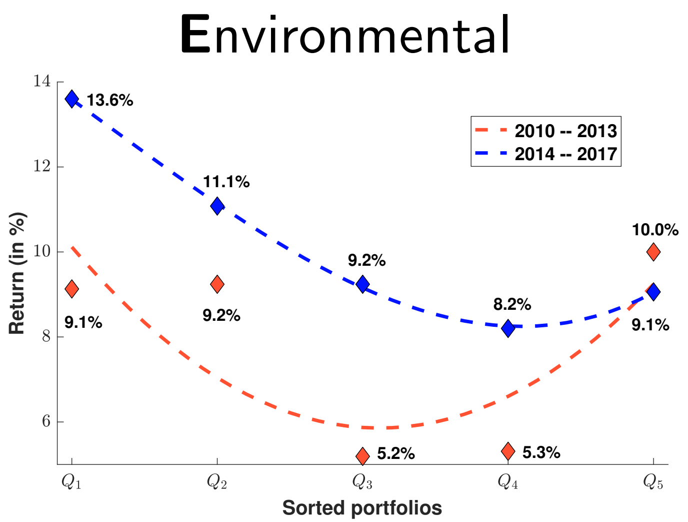
Governance

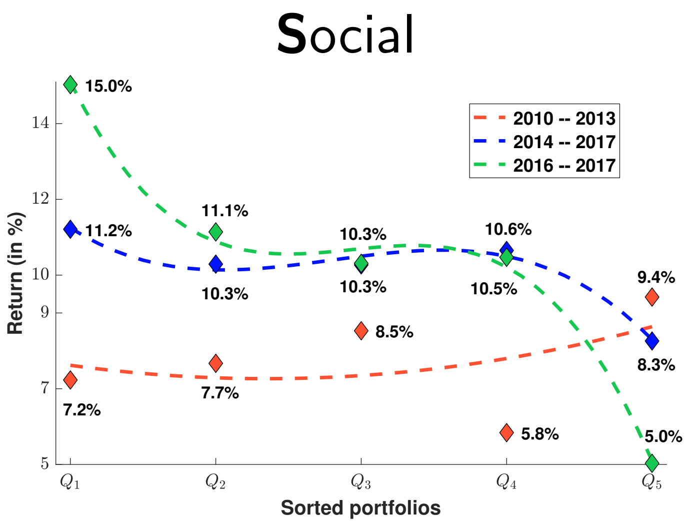


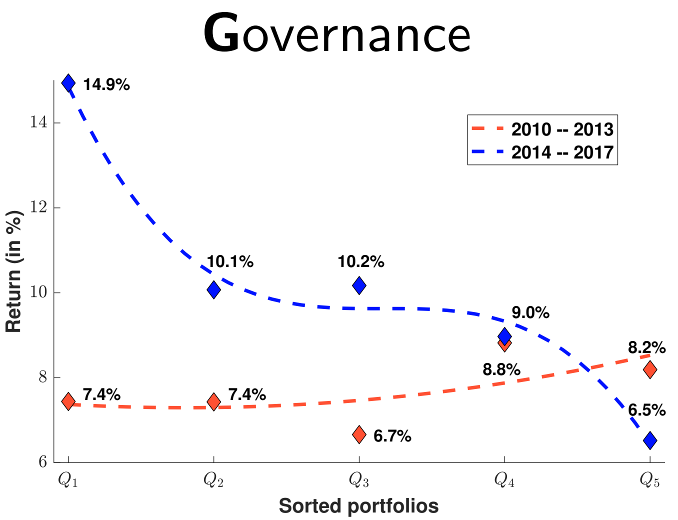
Source: Amundi Quantitative Research (2018)

Performance of ESG active management (2010 – 2017)

Eurozone







Source: Amundi Quantitative Research (2018)

Performance of ESG active management (2010 – 2017)

The 2014 break

Table 6: Summary of the results

Before 2014					
Factor	North America	Eurozone	Europe ex-EMU	Japan	World DM
ESG	−−	−	**0**	+	**0**
E	−	**0**	+	−	**0**
S	−	−	**0**	−	−
G	−	**0**	+	**0**	+
Since 2014					
Factor	North America	Eurozone	Europe ex-EMU	Japan	World DM
ESG	++	++	**0**	−	+
E	++	++	−	+	++
S	+	+	**0**	**0**	+
G	+	++	**0**	+	++

Source: Amundi Quantitative Research (2018)

The 2014 break

How to explain the 2014 break?

1. **The intrinsic value of ESG screening** or **the materiality of ESG**

   "Since we observe a feedback loop between extra-financial risks and asset pricing, we may also wonder whether the term 'extra' is relevant, because ultimately, we can anticipate that these risks may no longer be extra-financial, but simply financial" (Bennani et al., 2018).

   ESG risks $\Rightarrow$ Asset pricing

2. **The extrinsic value of ESG investing** or **the supply/demand imbalance**

   Investment flows matter!

The steamroller of ESG for institutional investors

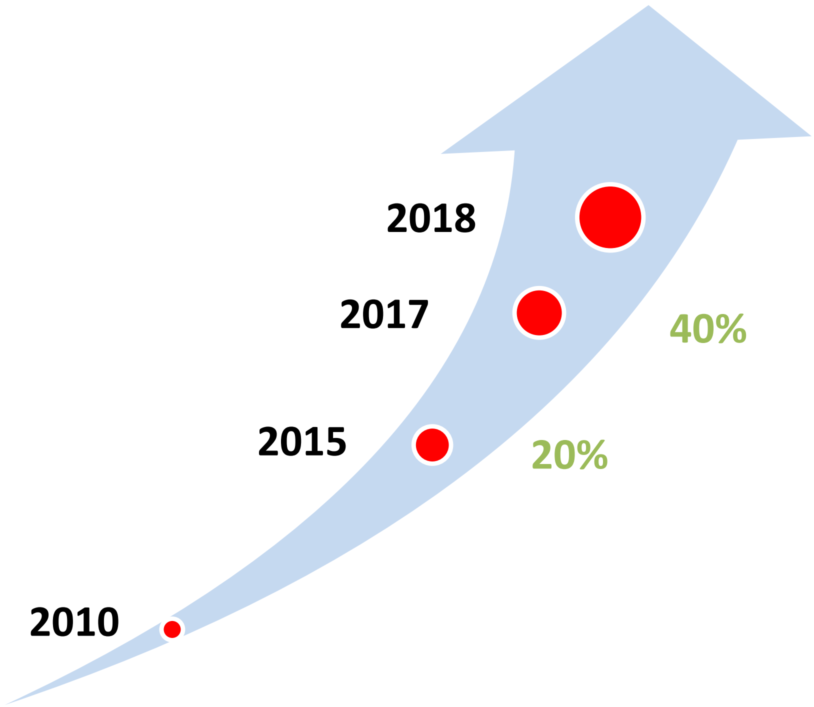


Figure 19: Frequency of institutional RFPs that require ESG filters

Source: Based on RFPs received at Amundi.

- In some countries, 100% of RFPs require ESG filters
- For some institutional investors, 100% of RFPs require ESG filters (public, para-public and insurance investors)
- For some strategies, 100% of RFPs require ESG filters (index tracking)

Passive management (optimized portfolios)

Portfolio optimization with a benchmark

We consider the following optimization problem[1]:

$$x^{\star}(\gamma) = \arg\min \frac{1}{2}\sigma^2(x \mid b) - \gamma \mathcal{S}(x \mid b)$$

where $\sigma(x \mid b)$ is the ex-ante tracking error (TE) of Portfolio x with respect to the benchmark b:

$$\sigma(x \mid b) = \sqrt{(x-b)^\top \Sigma (x-b)}$$

and $\mathcal{S}(x \mid b)$ is the excess score (ES) of Portfolio x wrt the benchmark b:

$$\begin{aligned} \mathcal{S}(x \mid b) &= (x-b)^\top \mathcal{S} \\ &= \mathcal{S}(x) - \mathcal{S}(b) \end{aligned}$$

[1] We note b the benchmark, $\mathcal{S}$ the vector of scores and Σ the covariance matrix.

Passive management (optimized portfolios)

Portfolio optimization with a benchmark

The objective is to find the optimal portfolio with the minimum TE for a given ESG excess score

This is a standard γ-problem where the expected returns are replaced by the ESG scores (see Lecture 1)

Performance of ESG passive management (2010-2017)

Arbitrage between ESG and TE

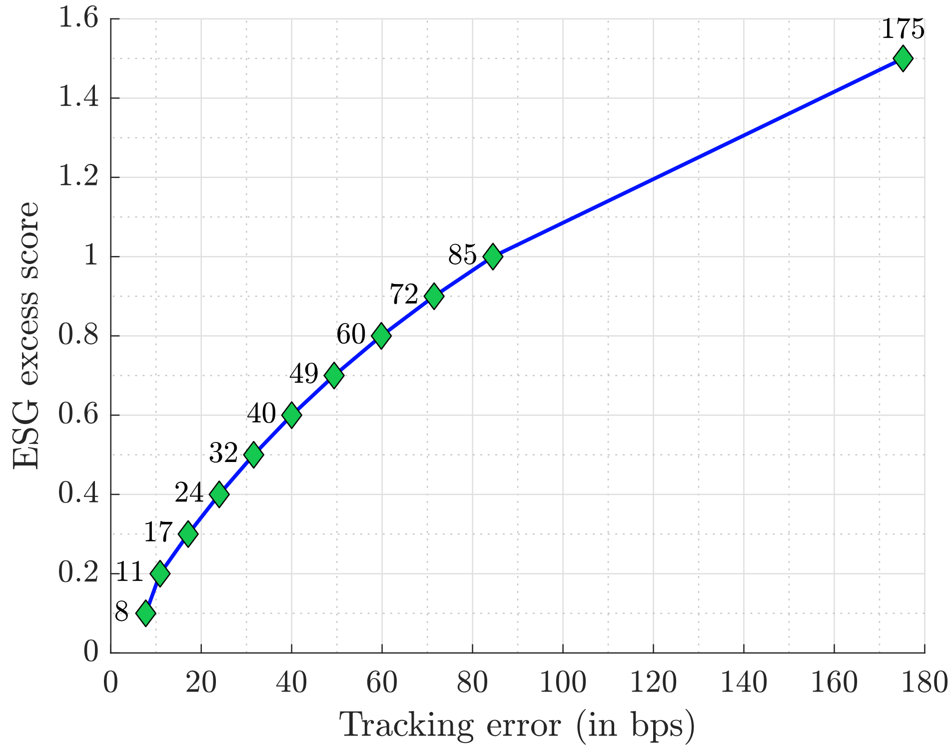


Figure 20: Efficient frontier of **ESG** optimized portfolios (World DM)

Source: Amundi Quantitative Research (2018)

No free lunch: **ESG investing implies to take a tracking-error risk!**

Performance of ESG passive management (2010-2017)

Performance of optimized portfolios

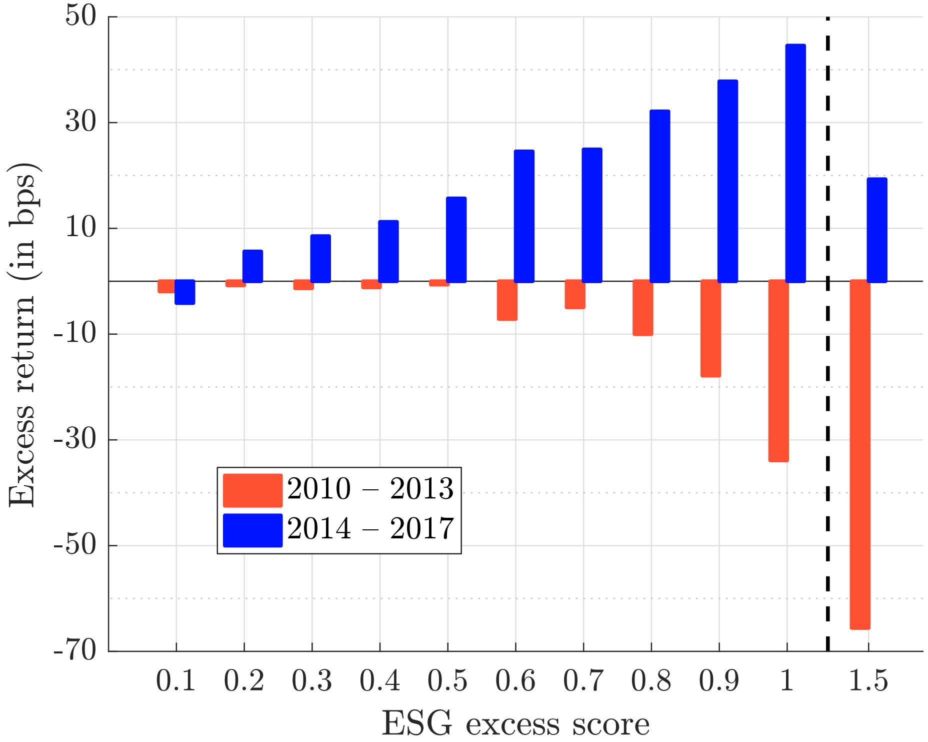


Figure 21: Annualized excess return of **ESG** optimized portfolios (World DM)

Source: Amundi Quantitative Research (2018)

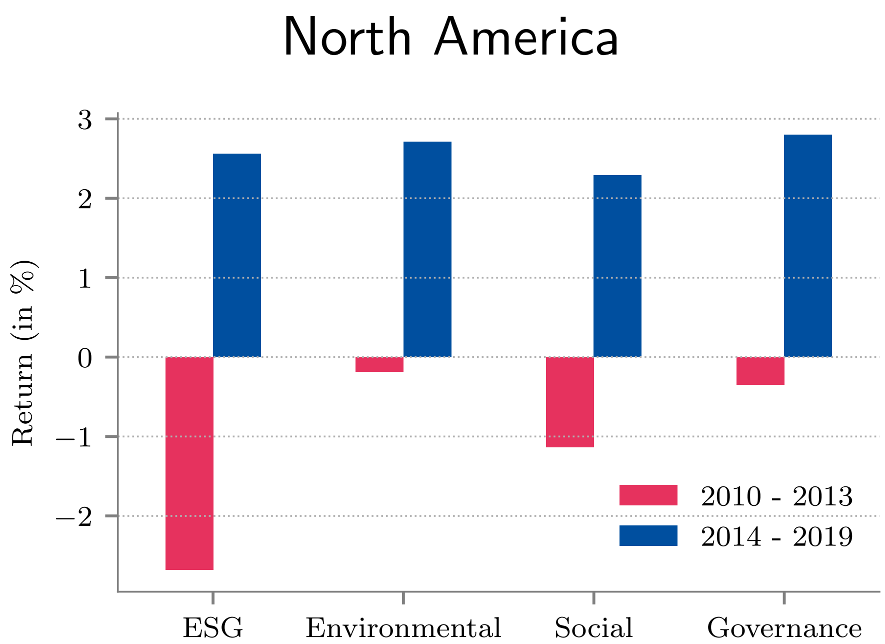
ESG investing & diversification: **Mind the gap**

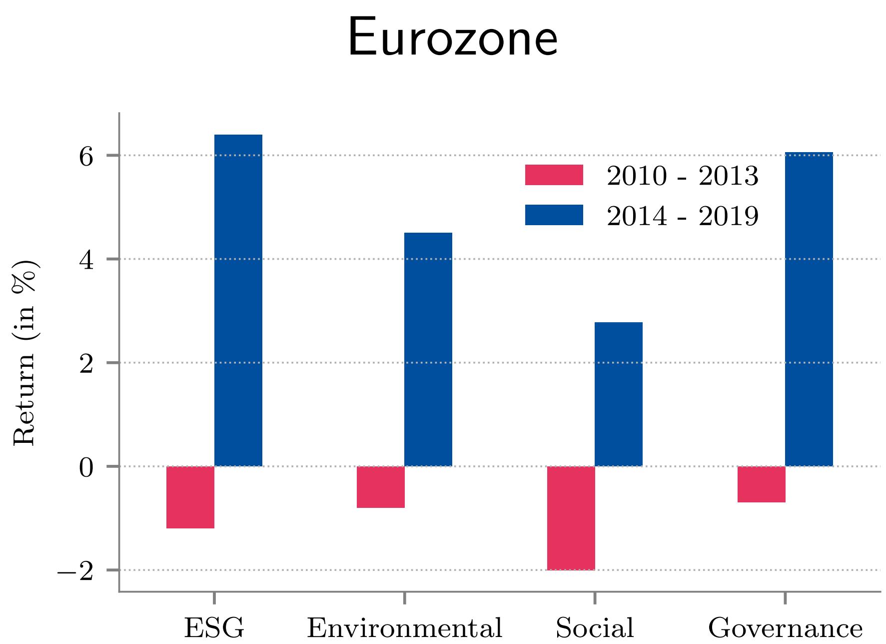
Performance of ESG active management (2018-2019)

On the road again

Main result

The 2018 – 2019 period seems to be a continuity of the 2014 – 2017 period rather than another distinctive phase





Source: Amundi Quantitative Research (2020)

Performance of ESG active management (2018-2019)

New findings in the stock market

1. **The transatlantic divide**

   $$\text{Eurozone} \succ \text{North America}$$

2. **Social: from laggard to leader**[2]

   $$\mathbf{S} \succ \mathbf{E}, \mathbf{G}$$

3. **ESG investing: growing in complexity**

   Beyond worst-in-class exclusion and best-in-class selection strategies

[2] In the Eurozone: 2010 – 2013: **E**, then 2014 – 2017: **G**, then 2018 – 2019: **S**
In North America: 2010 – 2013: **G**, then 2014 – 2017: **E**, then 2018 – 2019: **S**

Performance of ESG active management (2018-2019)

The transatlantic divide: the case of the Eurozone

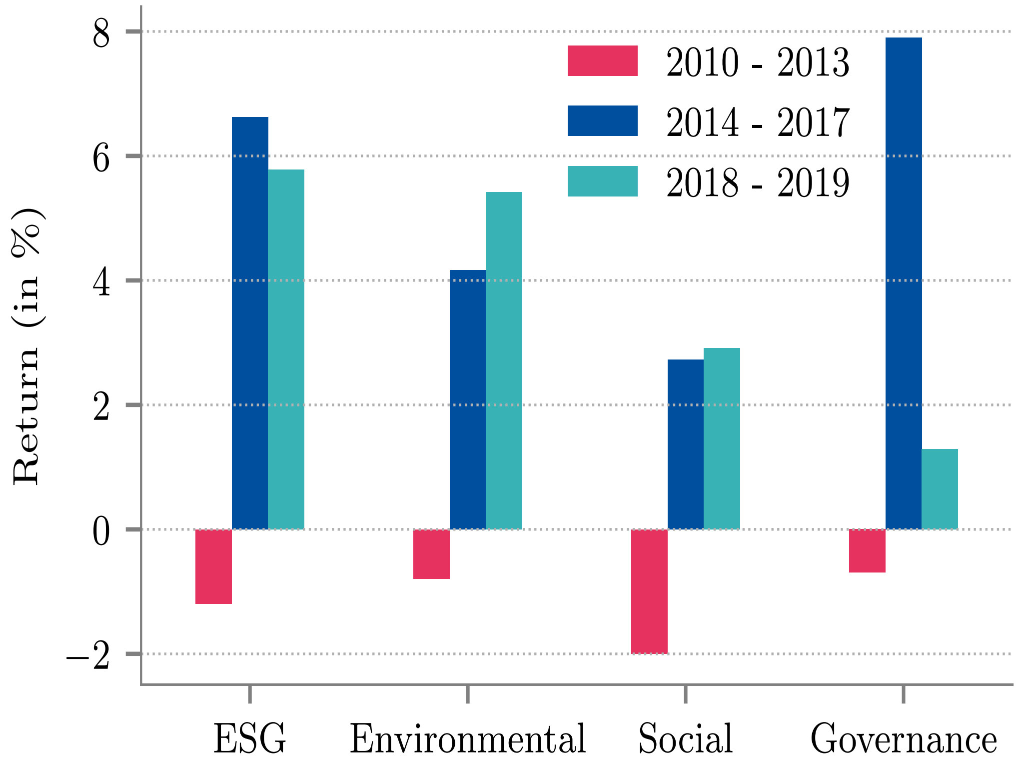


Figure 22: Annualized return of long/short $Q_1 - Q_5$ sorted portfolios

Source: Amundi Quantitative Research (2020)

⇒ Performance remains highly positive, and is improved for **E** and **S**

Performance of ESG active management (2018-2019)

The transatlantic divide: the case of North America

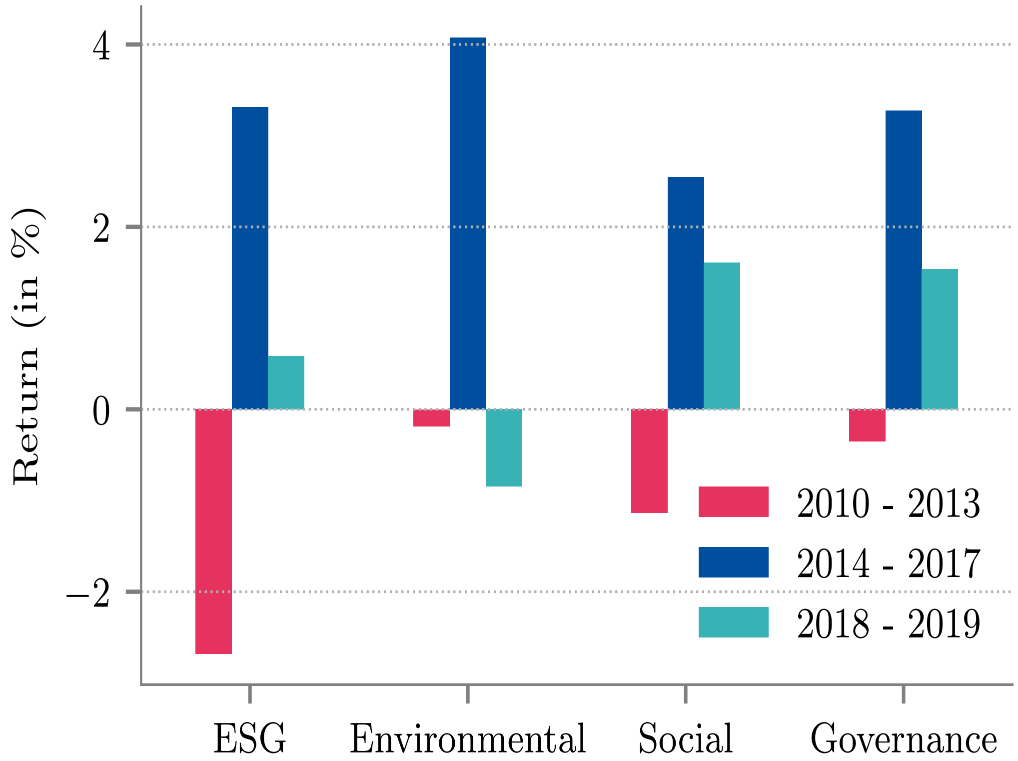


Figure 23: Annualized return of long/short $Q_1 - Q_5$ sorted portfolios

Source: Amundi Quantitative Research (2020)

$\Rightarrow$ Performance is positive, but reduced for **S** and **G**, whereas **E** is negative

Performance of ESG active management (2018-2019)

How to explain the American setback?

The regulatory value of ESG investing (or the intrinsic value *revisited*)

- Trump election effect
- Regulatory environment

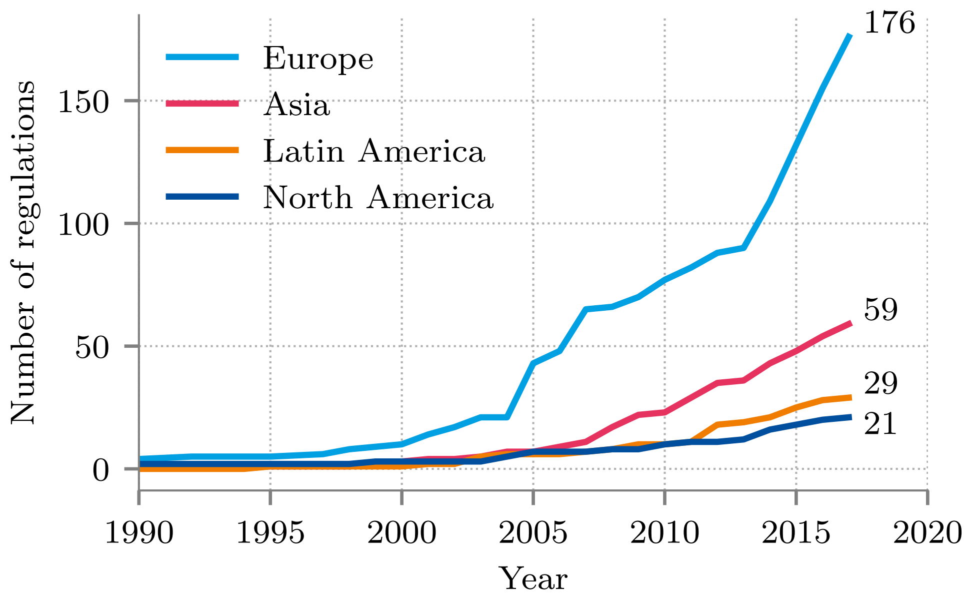


Figure 24: Number of ESG regulations

- ESG regulations are increasing, with a strong momentum in Europe but a weaker one in North America
- US withdrawal from Paris Climate Agreement

Source: PRI, responsible investment regulation database, 2019.

Performance of ESG active management (2018-2019)

How to explain the American setback?

The extrinsic value of ESG investing

- The 2014 break
  - November 2013: Responsible Investment and the Norwegian Government Pension Fund Global (2013 Strategy Council)
  - Strong mobilization of the largest institutional European investors: NBIM, APG, PGGM, ERAFP, FRR, etc.
  - They are massively invested in European stocks and America stocks:
    $$\text{NBIM} \succ \text{CalPERS} + \text{CalSTRS} + \text{NYSCRF for U.S. stocks}$$
- The 2018-2019 period
  - Implication of U.S. investors continues to be weak
  - Strong mobilization of medium (or tier two) institutional European investors, that have a low exposure on American stocks
  - Mobilization of European investors is not sufficient

$\Rightarrow$ The extrinsic value of ESG investing is temporary, and a new equilibrium will be found on the long run

Performance of ESG active management (2018-2019)

Social is strong in Eurozone

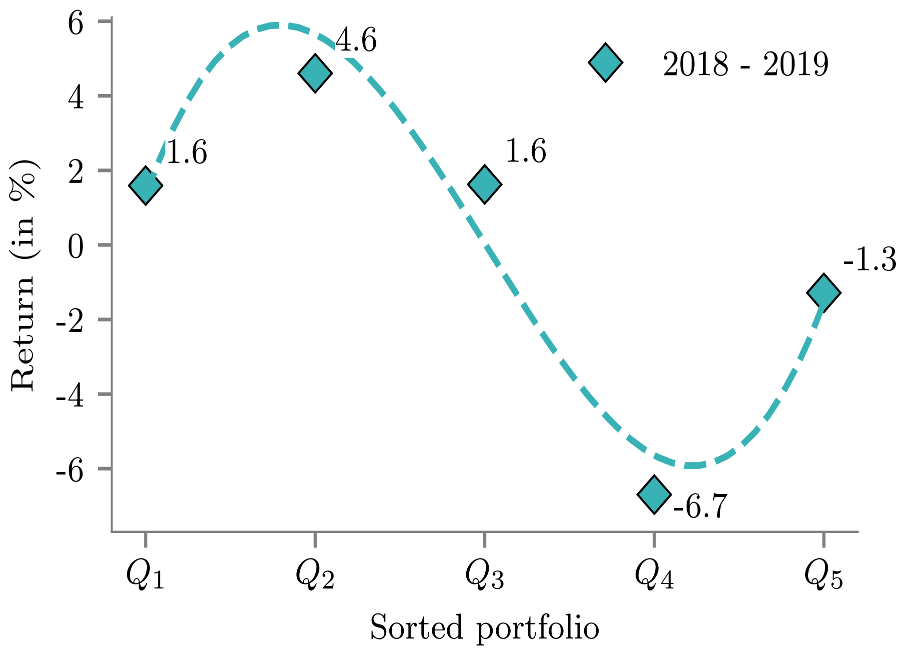


Figure 25: Sorted portfolios

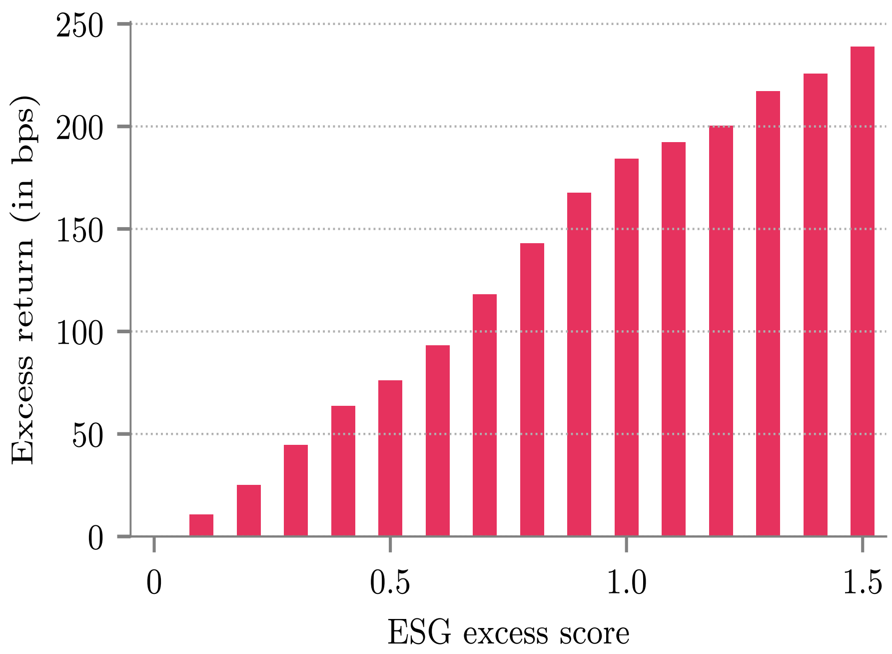


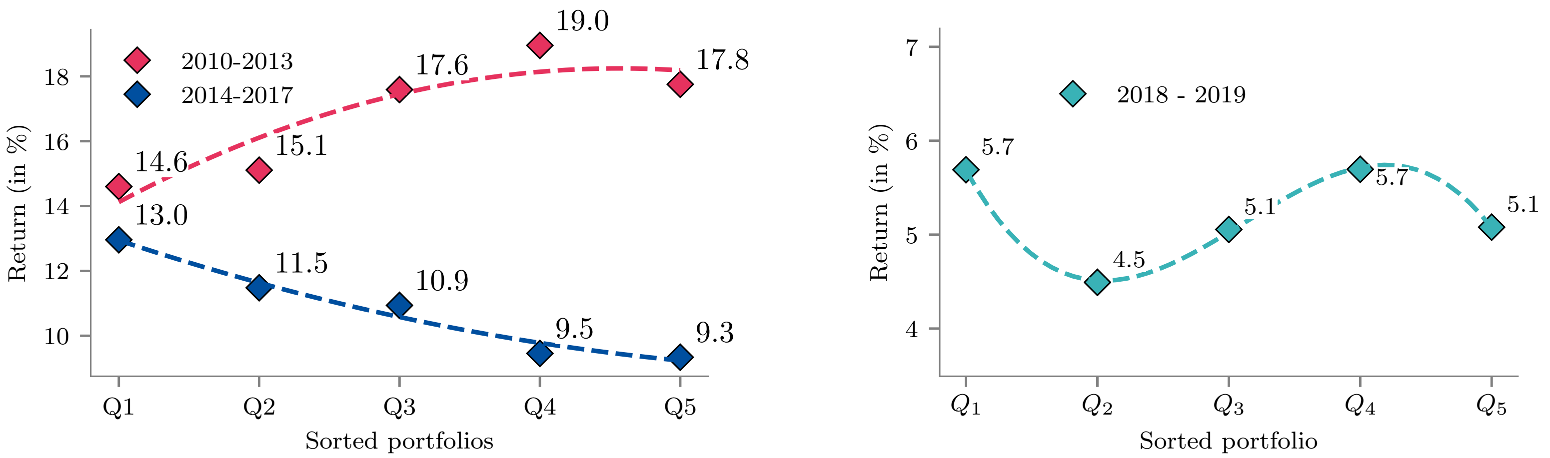
Figure 26: Optimized portfolios

Source: Amundi Quantitative Research (2020)

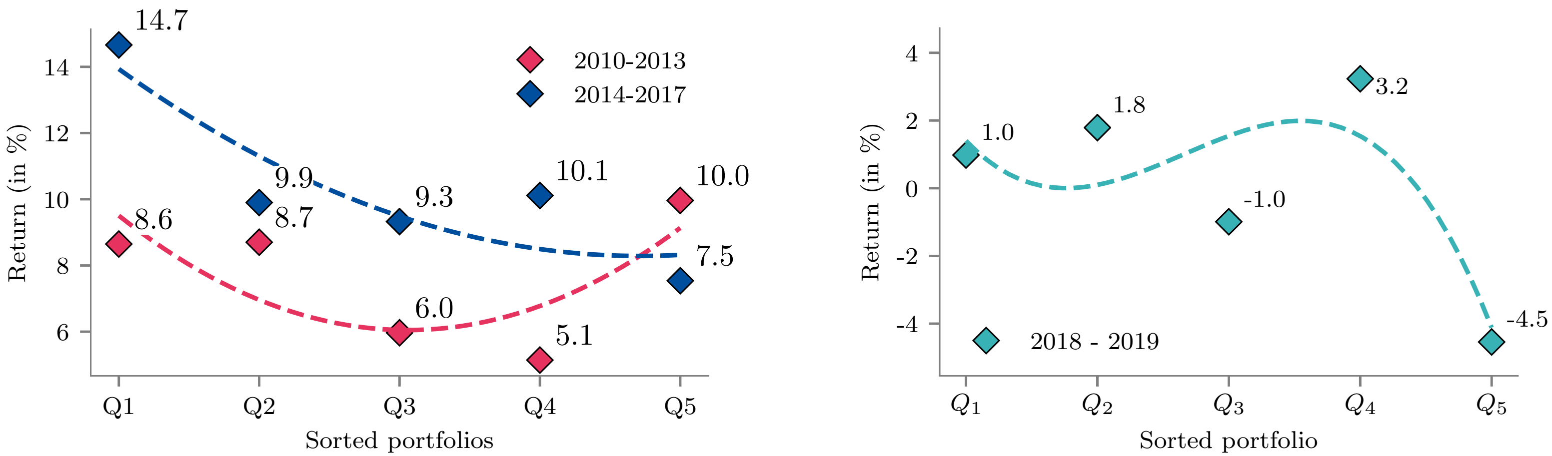
Performance of ESG active management (2018-2019)

ESG investing: growing in complexity

North America, **ESG**-Sorted portfolios, 2010 – 2019



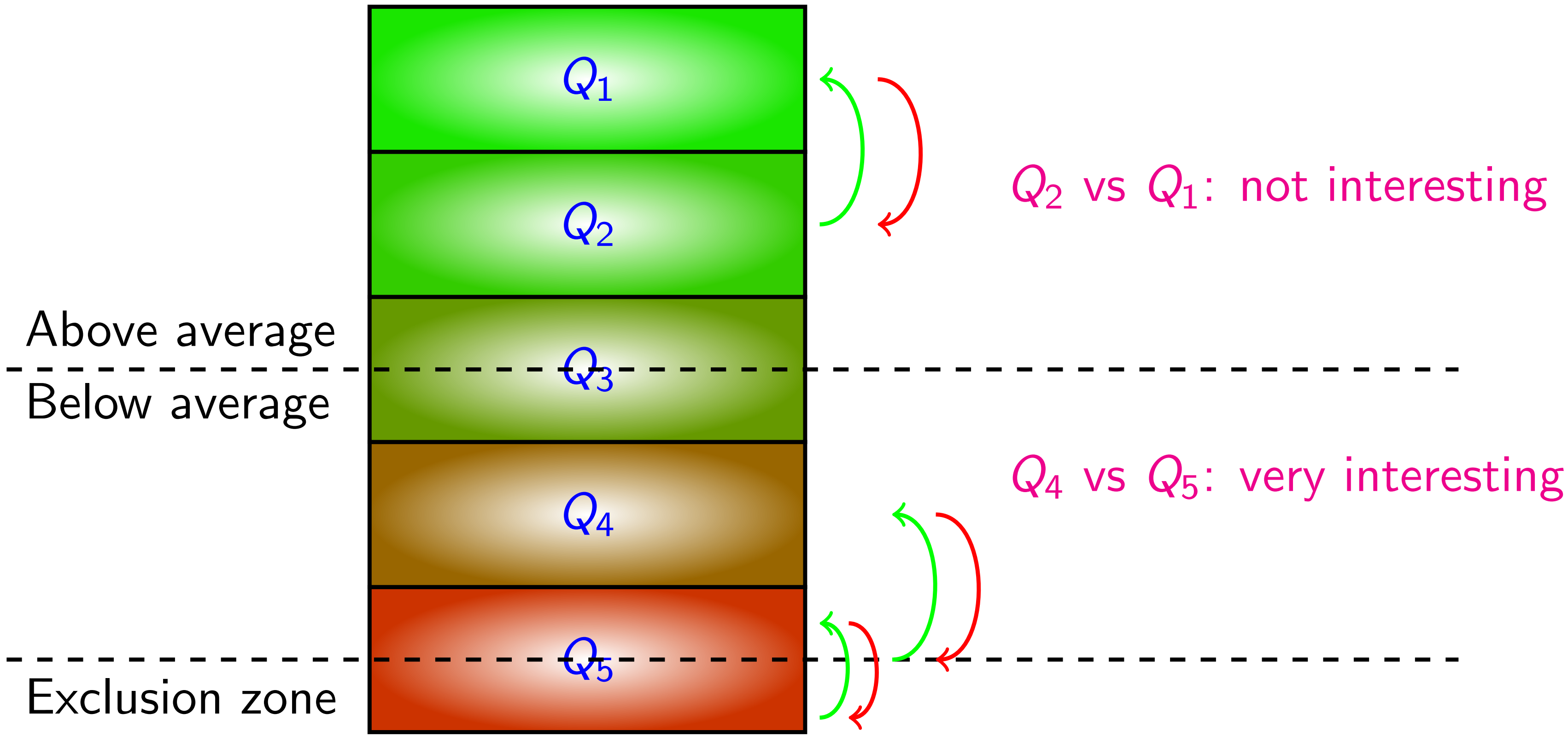
Eurozone, **ESG**-Sorted portfolios, 2010 – 2019



Performance of ESG active management (2018-2019)

The dynamic view of ESG investing

Figure 27: How to play ESG momentum?



ESG and factor investing

Single-factor model

Regression model

We have:

$$R_{i,t} = \alpha_i + \beta_i^j \mathcal{F}_{j,t} + \varepsilon_{i,t}$$

where $\mathcal{F}_{j,t}$ can be: market, size, value, momentum, low-volatility, quality or ESG.

ESG and factor investing

Single-factor model

Table 7: Results of cross-section regressions with long-only risk factors (average R^2)

Factor	North America 2010 – 2013	North America 2014 – 2019	Eurozone 2010 – 2013	Eurozone 2014 – 2019
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	40.1%	27.4%	42.6%	35.3%

Source: Amundi Quantitative Research (2020)

- Specific risk has increased during the period 2014 – 2019
- Since 2014, we find that:
  - ESG $\succ$ Value $\succ$ Quality $\succ$ Momentum $\succ \ldots$ (North America)
  - ESG $\succ$ Quality $\succ$ Momentum $\succ$ Value $\succ \ldots$ (Eurozone)

ESG and factor investing

Multi-factor model

Regression model

We have:

$$R_{i,t} = \alpha_i + \sum_{j}^{n_{\mathcal{F}}} \beta_i^j \mathcal{F}_{j,t} + \varepsilon_{i,t}$$

- 1F $=$ market
- 5F $=$ size $+$ value $+$ momentum $+$ low-volatility $+$ quality
- 6F $=$ 5F $+$ ESG

ESG and factor investing

Multi-factor model

Table 8: Results of cross-section regressions with long-only risk factors (average R^2)

Factor	North America		Eurozone	
	2010 – 2013	2014 – 2019	2010 – 2013	2014 – 2019
Market	40.8%	28.6%	42.8%	36.3%
5F model	46.1%	38.4%	49.5%	45.0%
6F model (5F + ESG)	46.7%	39.7%	50.1%	45.8%

Source: Amundi Quantitative Research (2020)

***p-value statistic for the MSCI Index (time-series, 2014 – 2019):

- 6F = ~~Size~~, Value, Momentum, Low-volatility, Quality, ~~ESG~~ (North America)
- 6F = Size, Value, Momentum, ~~Low-volatility~~, Quality, ESG (Eurozone)

ESG and factor investing

Factor selection

Least absolute shrinkage and selection operator (lasso)

The lasso regression is defined by:

$$
\begin{aligned}
\frac{y_i - \bar{y}}{\sigma_y} &= \sum_{k=1}^{K} \beta_k \left(\frac{x_{i,k} - \bar{x}_k}{\sigma_{x_k}} \right) + \varepsilon_i \\
\text{s.t.} & \quad \sum_{k=1}^{K} \left| \beta_k \right| \leq \tau
\end{aligned}
$$

We note $\hat{\beta}^{\text{lasso}}(\tau)$ the lasso estimator. We have $\hat{\beta}^{\text{lasso}}(\infty) = \hat{\beta}^{\text{ols}}$ and $\hat{\beta}^{\text{lasso}}(0) = \mathbf{0}_K$.

ESG and factor investing
Factor selection

In the two-asset case, we have:

$$\mathrm{RSS}\left(\beta_1, \beta_2\right) = \sum_{i=1}^{n} \left(\tilde{y}_i - \beta_1 \tilde{x}_{i,1} - \beta_2 \tilde{x}_{2,1}\right)^2$$

If we consider the equation $\mathrm{RSS}\left(\beta_1, \beta_2\right) = c$, we obtain the following cases:

$c < \mathrm{RSS}\left(\hat{\beta}_1^{\mathrm{ols}}, \hat{\beta}_2^{\mathrm{ols}}\right)$	$c = \mathrm{RSS}\left(\hat{\beta}_1^{\mathrm{ols}}, \hat{\beta}_2^{\mathrm{ols}}\right)$	$c > \mathrm{RSS}\left(\hat{\beta}_1^{\mathrm{ols}}, \hat{\beta}_2^{\mathrm{ols}}\right)$
No solution	One solution $\left(\hat{\beta}_1^{\mathrm{ols}}, \hat{\beta}_2^{\mathrm{ols}}\right)$	An ellipsoid

What does this result become when imposing the lasso constraint $\left|\beta_1\right| + \left|\beta_2\right| \leq \tau$?

Sparsity property

$$\exists\, \eta > 0 : \forall \tau < \eta,\ \min\left(\left|\hat{\beta}_1^{\mathrm{lasso}}\right|, \left|\hat{\beta}_2^{\mathrm{lasso}}\right|\right) = 0$$

ESG and factor investing

Factor selection

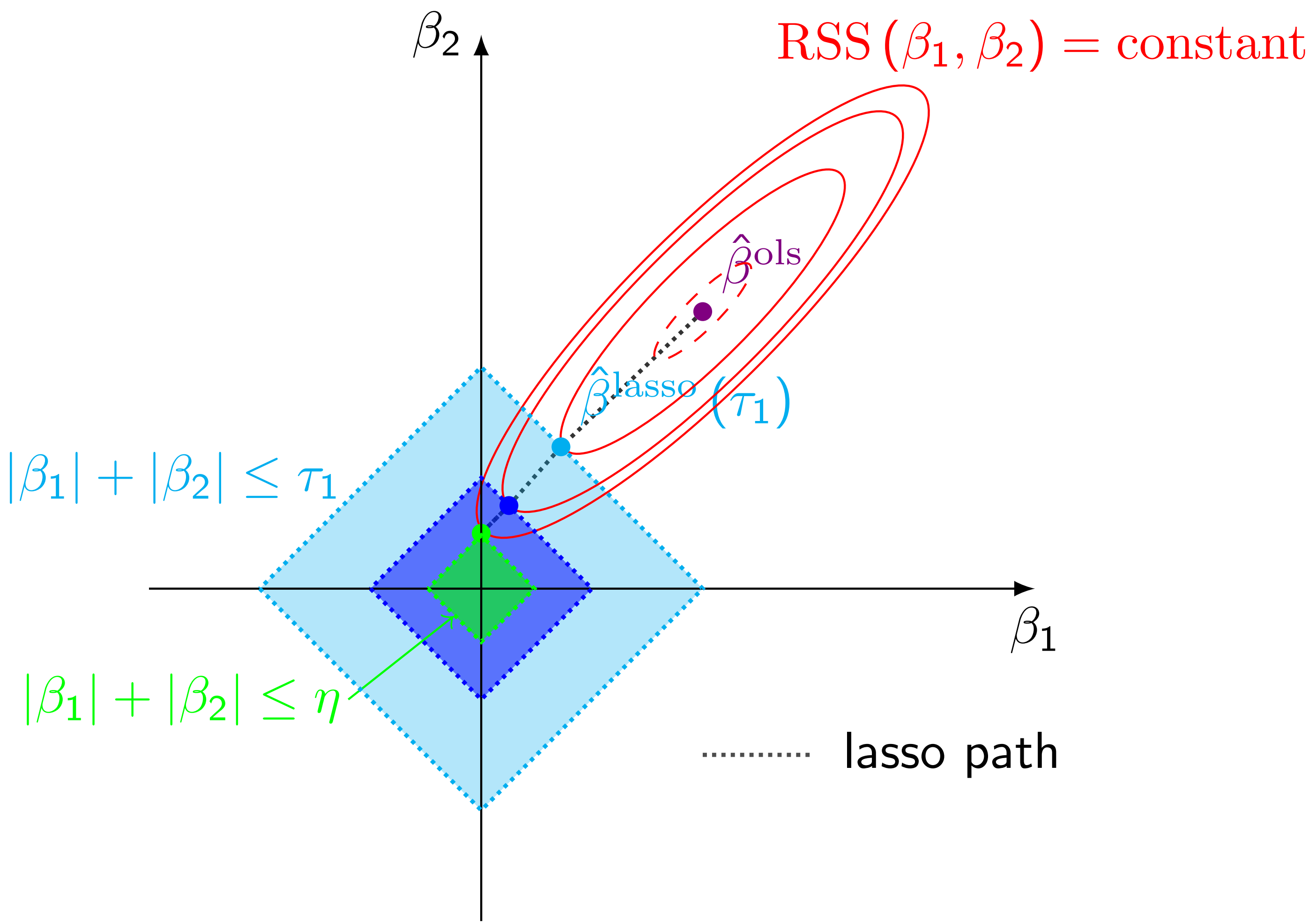


Figure 28: Interpretation of the lasso regression

Factor selection

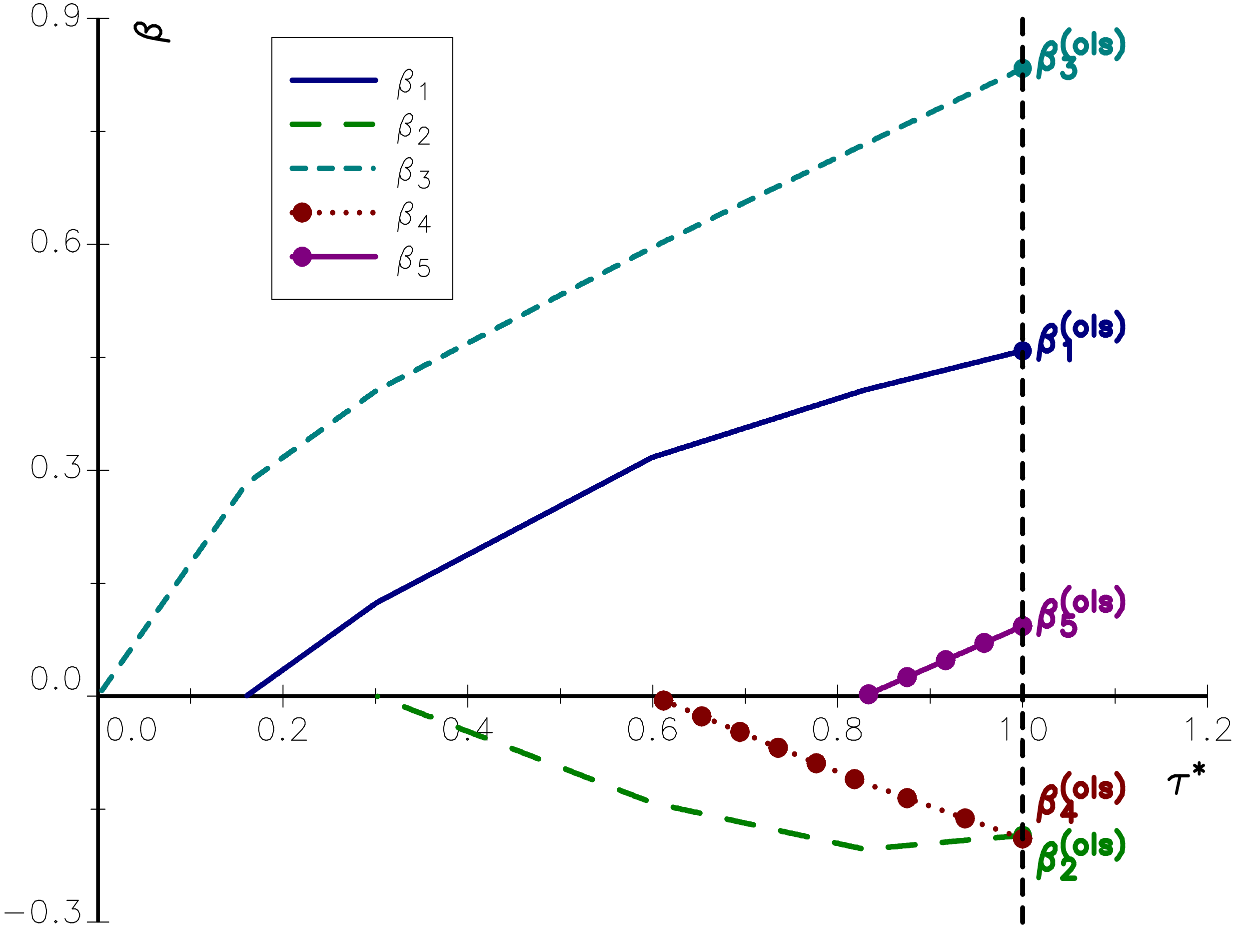


Figure 29: Variable selection with the lasso method (variable ordering: $x_3 \succ x_1 \succ x_2 \succ x_4 \succ x_5$)

ESG and factor investing

ESG as an alpha strategy

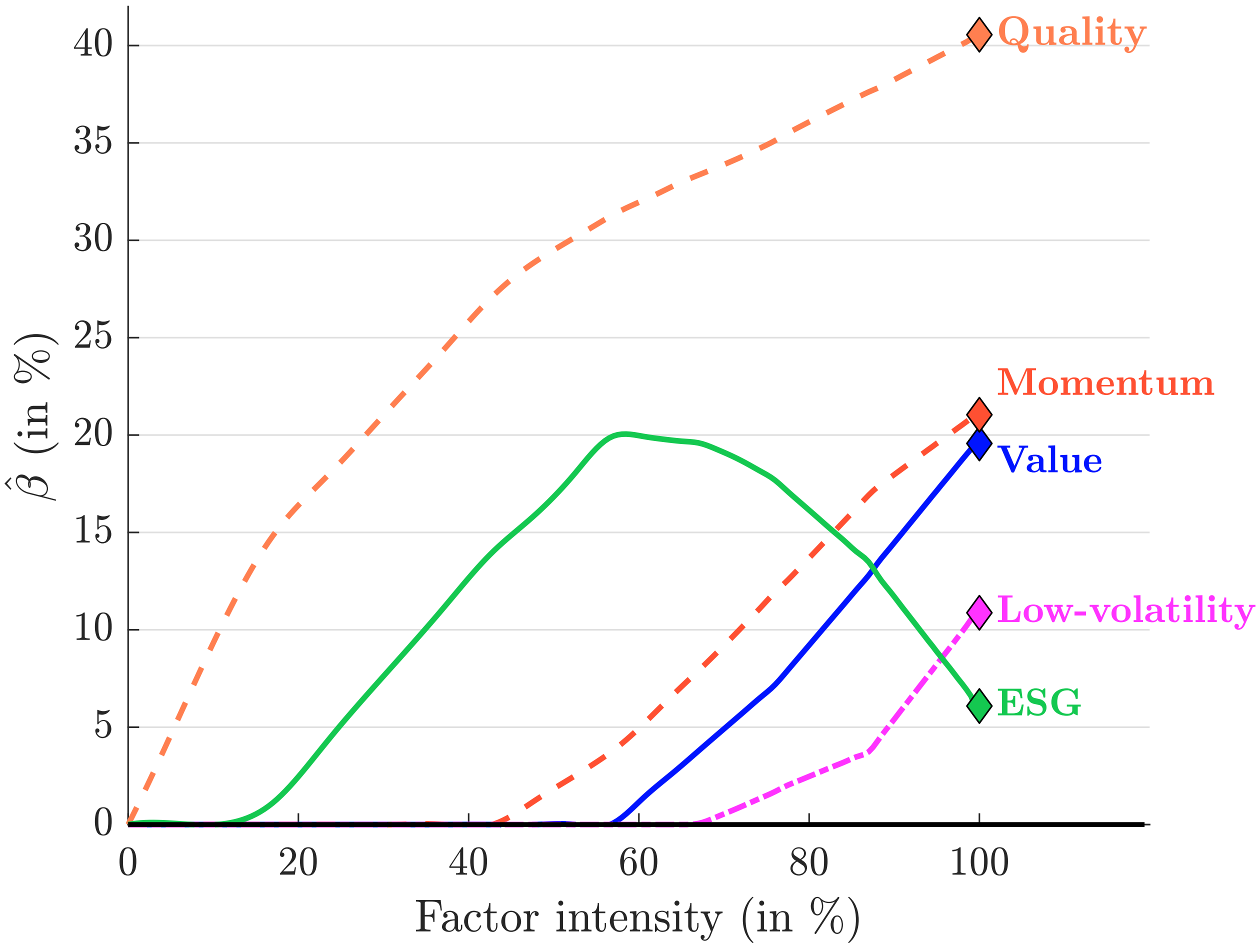


Figure 30: Factor selection (North America)

Source: Amundi Quantitative Research (2020)

ESG and factor investing

ESG as a beta strategy

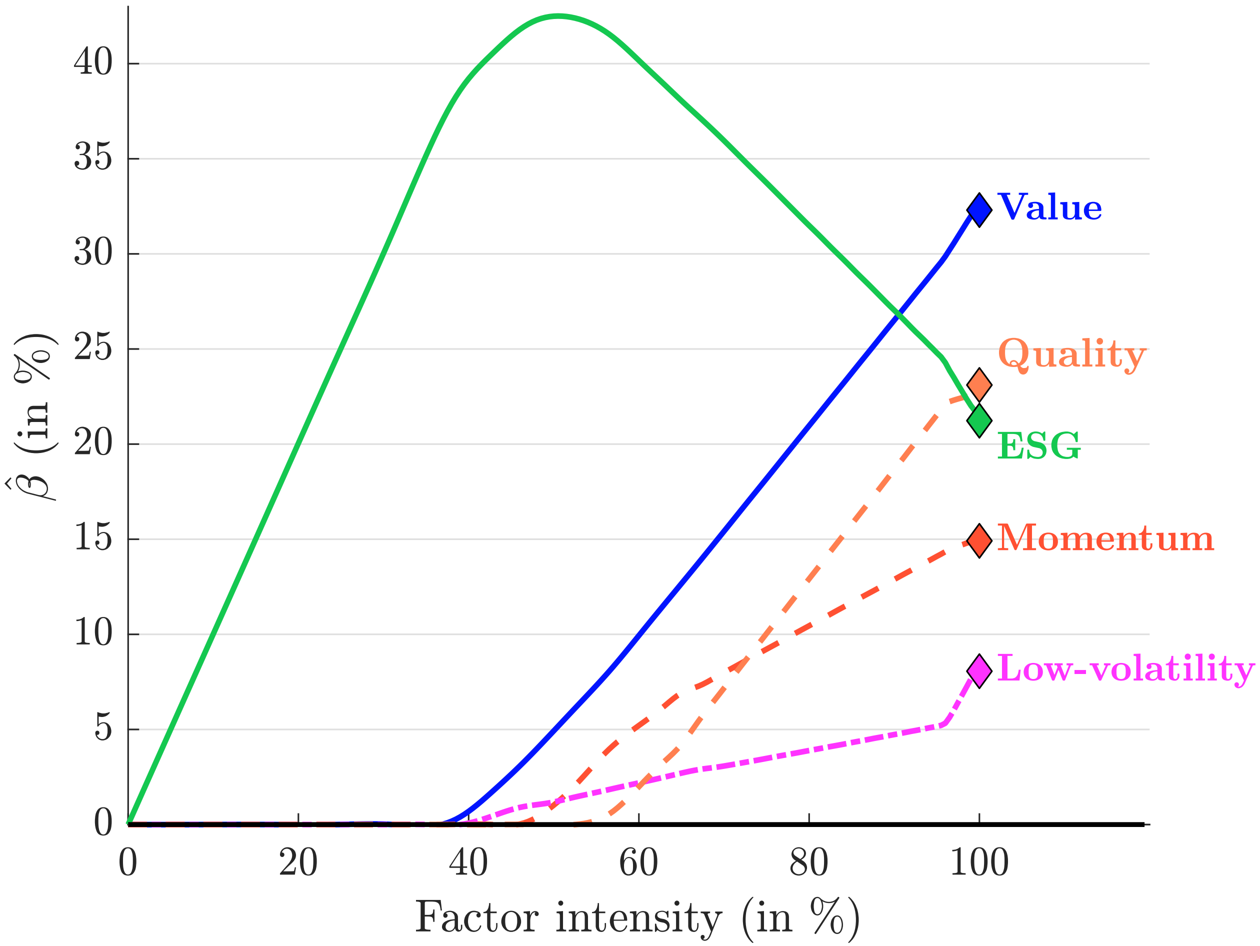


Figure 31: Factor selection (Eurozone)

Source: Amundi Quantitative Research (2020)

ESG and factor investing

What is the difference between alpha and beta?

α or β?

"[...] When an alpha strategy is massively invested, it has an enough impact on the structure of asset prices to become a risk factor.
[...] 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" (Roncalli, 2020)

- ESG remains an alpha strategy in North America
- ESG becomes a beta strategy (or a risk factor) in Europe

Why ESG investing in bond markets is different than ESG investing in stock markets

Stocks

- ESG scoring is incorporated in portfolio management
- ESG = long-term business risk $\Rightarrow$ strongly impacts the equity
- Portfolio integration
- Managing the business risk

Bonds

- ESG integration is generally limited to exclusions
- ESG lowly impacts the debt
- Portfolio completion
- Fixed income = impact investing
- Development of pure play ESG securities (green and social bonds)

$\Rightarrow$ Stock holders are more ESG sensitive than bond holders because of the capital structure

Why ESG investing in bond markets is different than ESG investing in stock markets

ESG investment flows affect asset pricing differently

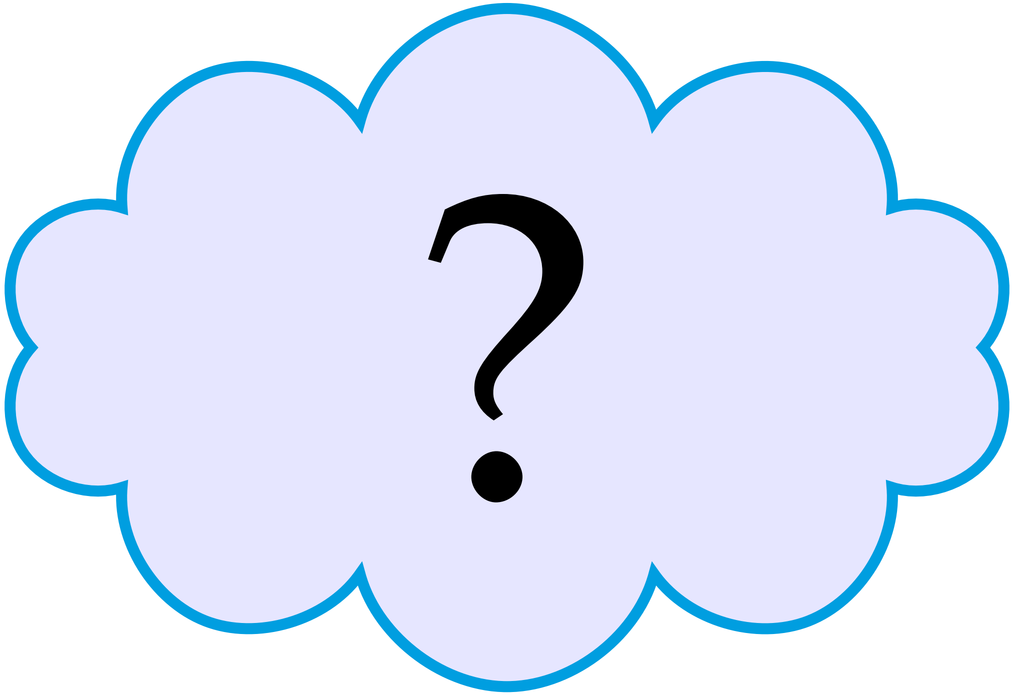
- Impact on carry (coupon effect)?
- Impact on price dynamics (credit spread/mark-to-market effect)?
- Buy-and-hold portfolios $\neq$ managed portfolios

The distinction between IG and HY bonds

- ESG and credit ratings are correlated
- There are more worst-in-class issuers in the HY universe, and best-in-class issuers in the IG universe
- Non-neutrality of the bond universe (bonds $\neq$ stocks)

What is the performance of ESG investing?

Academic findings



What is the performance of ESG investing?

We consider the two studies conducted by Amundi Quantitative Research:

- Ben Slimane, M., Le Guenedal, T., Roncalli, T., and Sekine T. (2020), ESG Investing in Corporate Bonds: Mind the Gap, Amundi Working Paper, WP-94-2019, `https://research-center.amundi.com`
- Ben Slimane, M., Brard, E., Le Guenedal, T., Roncalli, T., and Sekine T. (2020), ESG Investing in Fixed Income: It's Time To Cross the Rubicon, Amundi Discussion Paper, DP-45-2019, `https://research-center.amundi.com`

Sorted portfolio methodology

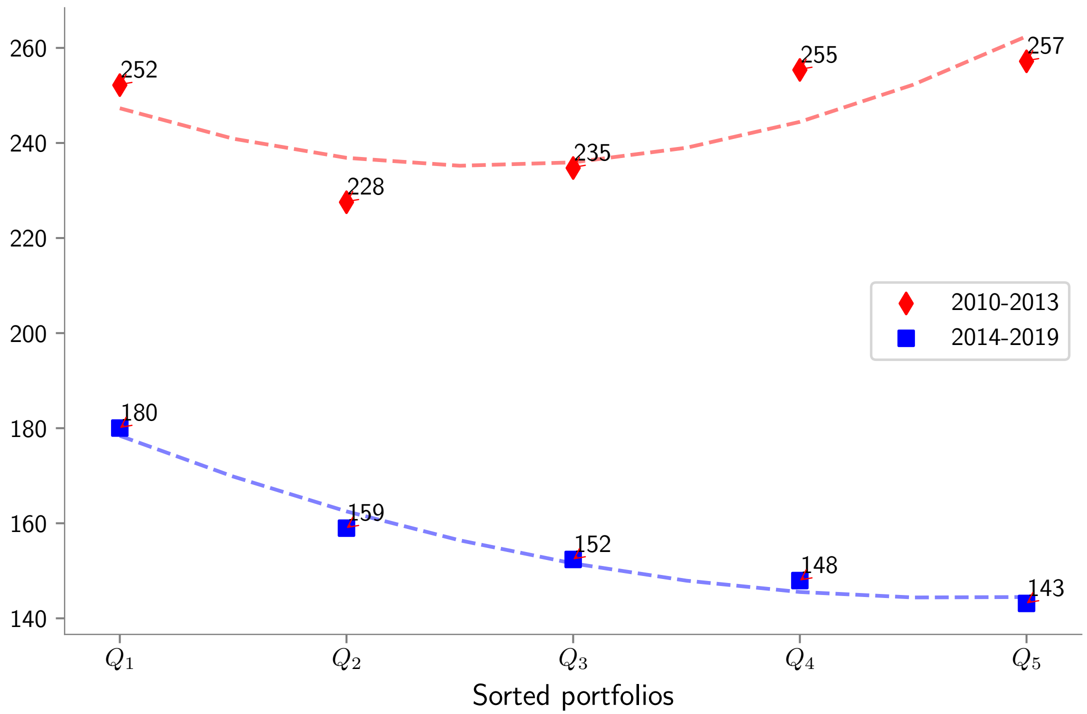
Sorted-portfolio approach

- Sorted-based approach of Fama-French (1992)
- At each rebalancing date t, we rank the bonds according to their Amundi **ESG** z-score
- We form the five quintile portfolios Q_i for $i = 1, \ldots, 5$
- The portfolio Q_i is invested during the period $]t, t+1]$:
  - Q_1 corresponds to the best-in-class portfolio (best scores)
  - Q_5 corresponds to the worst-in-class portfolio (worst scores)
- Monthly rebalancing
- Universe: ICE (BofAML) Large Cap IG EUR Corporate Bond
- Sector-weighted and sector-neutral portfolio
- Within a sector, bonds are equally-weighted

What is the performance of ESG investing?

Sorted portfolios

Figure 32: Annualized credit return in bps of **ESG** sorted portfolios (EUR IG, 2010 – 2019)



Source: Amundi Quantitative Research (2020)

Table 9: Carry statistics (in bps)

Period	Q_1	Q_5
2010-2013	175	192
2014-2019	113	128

- Negative carry (coupon level)
- Positive mark-to-market (dynamics of credit spreads and bond prices)

Bond portfolio optimization

We consider the following optimization problem:

$$x^{\star}(\gamma) = \arg\min \mathcal{R}(x \mid b) - \gamma \cdot \mathcal{S}(x \mid b)$$

where:

$$\mathcal{R}(x \mid b) = \frac{1}{2}\mathcal{R}_{\mathrm{MD}}(x \mid b) + \frac{1}{2}\mathcal{R}_{\mathrm{DTS}}(x \mid b)$$

and:

- $\mathcal{R}_{\mathrm{MD}}(x \mid b)$ and $\mathcal{R}_{\mathrm{DTS}}(x \mid b)$ are the interest rate and credit **active risk** measures wrt the benchmark b
- $\mathcal{S}(x \mid b)$ is the ESG excess score of Portfolio x wrt the benchmark b

The objective is to find the optimal portfolio minimizing interest rate and credit active risk for a given ESG excess score

What is the performance of ESG investing?

Optimized portfolios

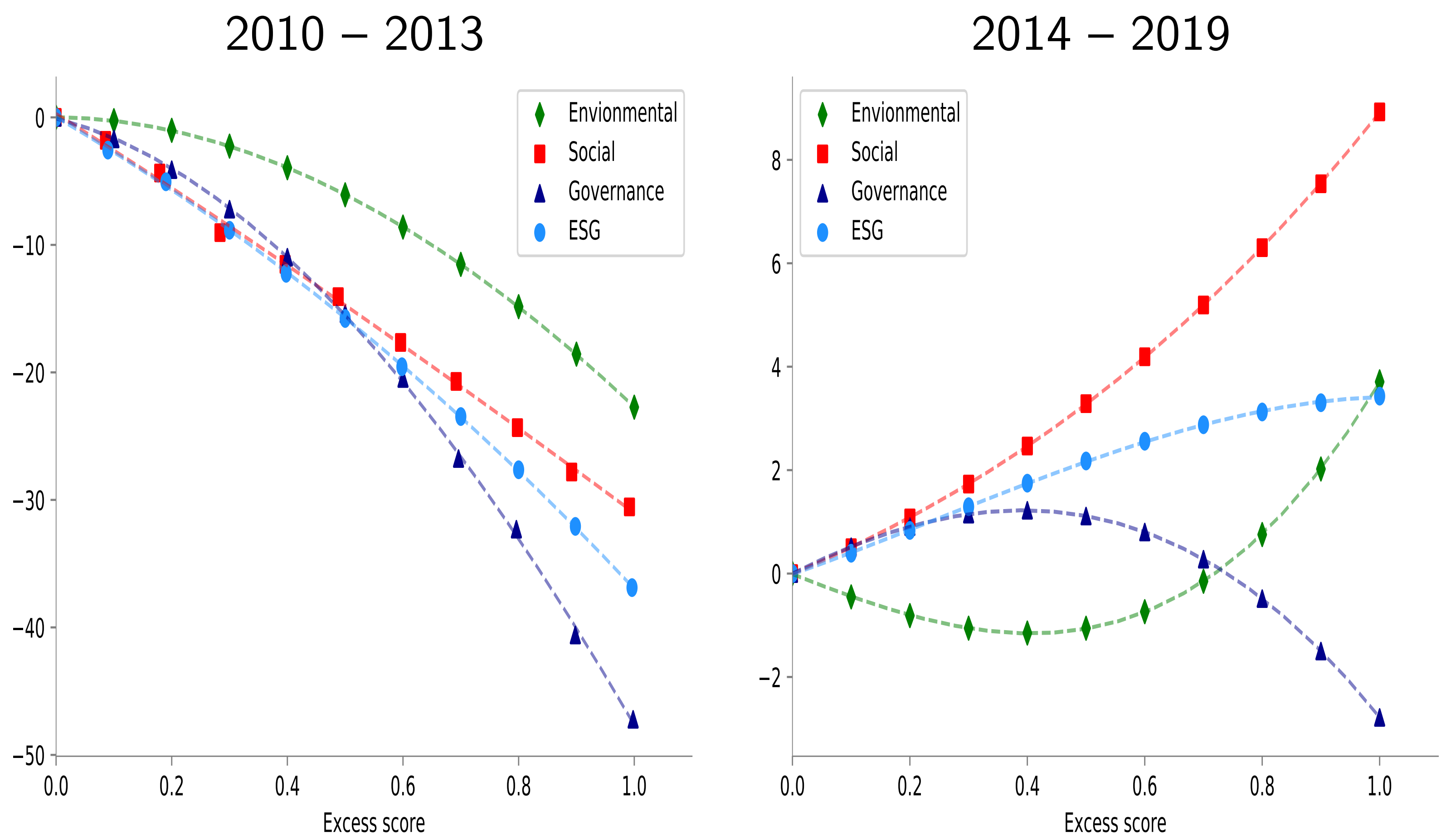


Figure 33: Excess credit return in bps of optimized portfolios (EUR IG)

Source: Amundi Quantitative Research (2020)

What is the performance of ESG investing?

Optimized portfolios

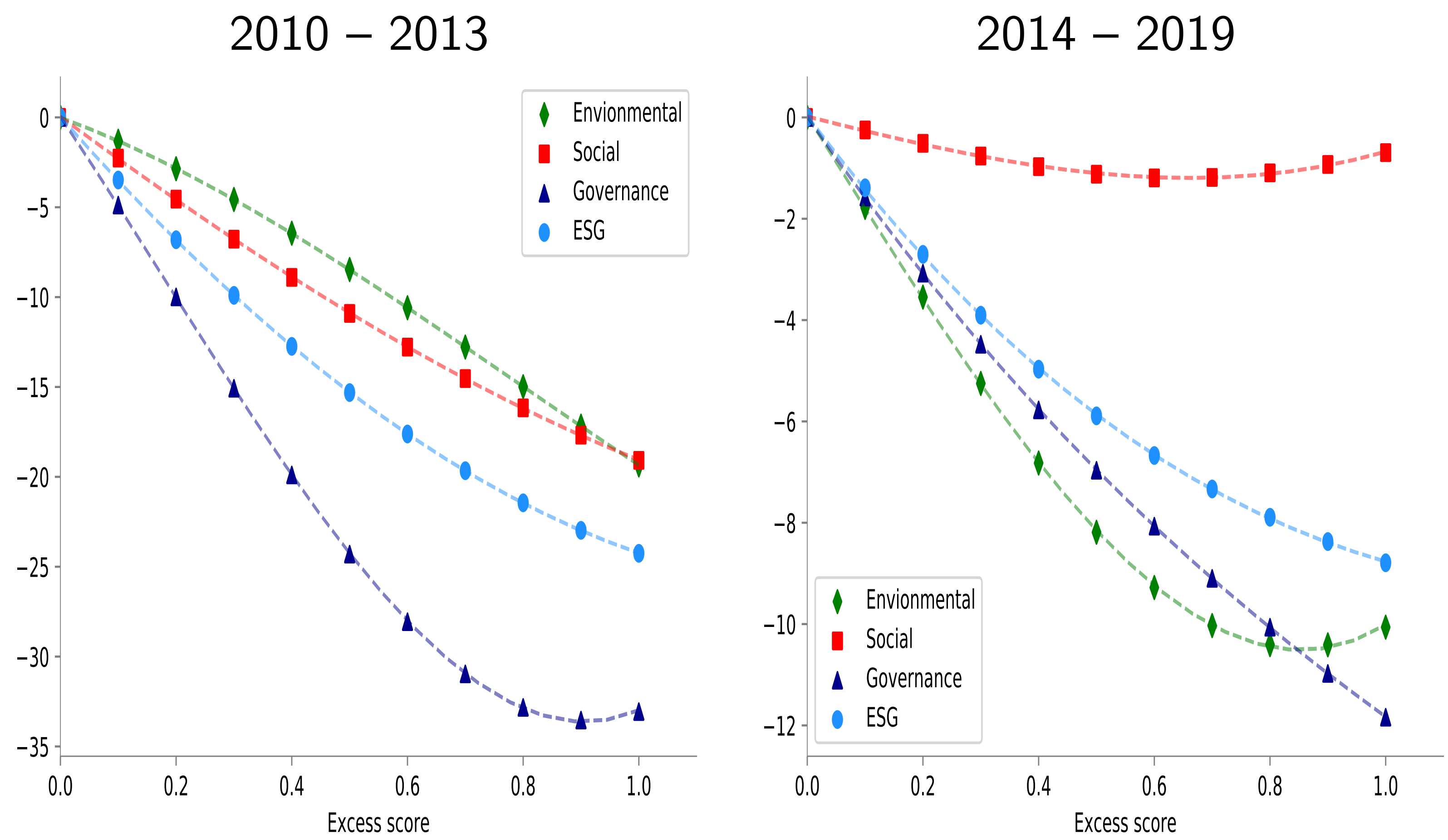


Figure 34: Excess credit return in bps of optimized portfolios (USD IG)

Source: Amundi Quantitative Research (2020)

The impact of ESG on the funding cost

An integrated Credit-ESG model

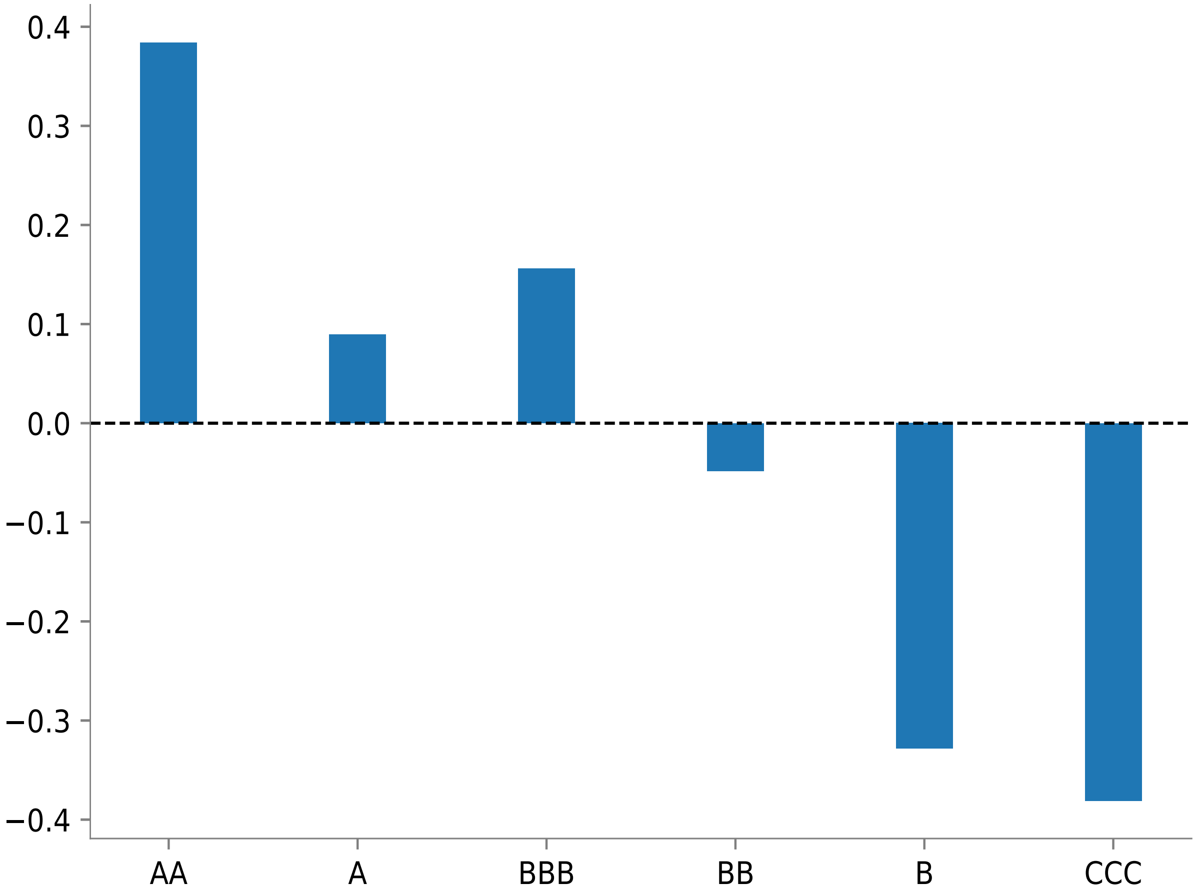


Figure 35: Average **ESG** score with respect to the credit rating (2010 – 2019)

Source: Amundi Quantitative Research (2020)

The impact of ESG on the funding cost
An integrated Credit-ESG model

We consider the following regression model:

$$\begin{aligned}\ln \mathrm{OAS}_{i,t} &= \alpha_t + \beta_{esg} \cdot \mathcal{S}_{i,t} + \beta_{md} \cdot \mathrm{MD}_{i,t} + \sum_{j=1}^{N_{\mathcal{S}ector}} \beta_{\mathcal{S}ector}(j) \cdot \mathcal{S}ector_{i,t}(j) + \\ & \beta_{sub} \cdot \mathrm{SUB}_{i,t} + \sum_{k=1}^{N_{\mathcal{R}ating}} \beta_{\mathcal{R}ating}(k) \cdot \mathcal{R}ating_{i,t}(k) + \varepsilon_{i,t}\end{aligned}$$

where:

- $\mathcal{S}_{i,t}$ is the **ESG** z-score of Bond i at time t
- $\mathrm{SUB}_{i,t}$ is a dummy variable accounting for subordination of the bond
- $\mathrm{MD}_{i,t}$ is the modified duration
- $\mathcal{S}ector_{i,t}(j)$ is a dummy variable for the j^{th} sector
- $\mathcal{R}ating_{i,t}(k)$ is a dummy variable for the k^{th} rating

The impact of ESG on the funding cost

An integrated Credit-ESG model

Table 10: Results of the panel data regression model (EUR IG, 2010 – 2019)

	2010–2013				2014–2019			
	ESG	**E**	**S**	**G**	**ESG**	**E**	**S**	**G**
R^2	60.0%	59.4%	59.5%	60.3%	66.3%	65.0%	65.2%	64.6%
Excess R^2 of ESG	0.6%	0.0%	0.2%	1.0%	4.0%	2.6%	2.9%	2.3%
$\hat{\beta}_{esg}$	-0.05	-0.01	-0.02	-0.07	-0.09	-0.08	-0.08	-0.08
t-statistic	-32	-7	-16	-39	-124	-98	-104	-92

Source: Amundi Quantitative Research (2020)

The assumption $\mathcal{H}_0 : \beta_{esg} < 0$ is not rejected

The impact of ESG on the funding cost

ESG cost of capital with min/max score bounds

We calculate the difference between:

(1) the funding cost of **the worst-in-class issuer** and

(2) the funding cost of **the best-in-class issuer**

by assuming that:

- the two issuers have the same credit rating;
- the two issuers belong to the same sector;
- the two issuers have the same capital structure;
- the two issuers have the same debt maturity.

$\Rightarrow$ Two approaches:

1. Theoretical approach: ESG scores are set to -3 and $+3$ (not realistic)
2. Empirical approach: ESG scores are set to observed min/max score bounds (e.g. min/max $= -2.0/+1.9$ for Consumer Cyclical A-rated EUR, $-2.1/+3.2$ for Banking A-rated EUR, etc.)

The impact of ESG on the funding cost

ESG cost of capital with min/max score bounds

Table 11: **ESG** cost of capital (IG, 2014 – 2019)

	EUR				USD			
	AA	A	BBB	Average	AA	A	BBB	Average
Banking	23	45	67	45	11	19	33	21
Basic	9	25	44	26	5	15	34	18
Capital Goods	8	32	42	27	6	15	26	16
Communication		26	48	37	5	11	23	13
Consumer Cyclical	3	26	43	28	2	8	17	10
Consumer Non-Cyclical	15	29	31	25	6	12	19	12
Utility & Energy	12	32	56	33	9	14	31	18
Average	12	31	48	**31**	7	13	26	**15**

Source: Amundi Quantitative Research (2020)

ESG investing versus ESG financing

- Markowitz, H. (1952), Portfolio Selection, *Journal of Finance*, 7(1), pp. 77-91.
- Modigliani, F., and Miller, M.H. (1958), The Cost of Capital, Corporation Finance and the Theory of Investment, *American Economic Review*, 48(3), pp. 261-297.

$\Rightarrow$ Two misunderstandings:

1. Capital allocation & asset allocation
2. Cost of capital & asset (stock/bond) return

Prologue

"*There is no Plan B, because there is no Planet B*"

Ban Ki-moon, UN Secretary-General, September 2014

Is it a question of climate-related issues?

In fact, it is more an economic growth issue

"*The Golden Rule of Accumulation: A Fable for Growthmen*"

Edmund Phelps, *American Economic Review*, 1961
Nobel Prize in Economics, 2006

Climate risks and financial losses

Climate risks transmission channels to financial stability

- The **physical risks** that arise from the increased frequency and severity of climate and weather related events that damage property and disrupt trade
- The **liability risks** stemming from parties who have suffered loss from the effects of climate change seeking compensation from those they hold responsible
- The **transition risks** that can arise through a sudden and disorderly adjustment to a low carbon economy

Speech by Mark Carney at the International Climate Risk Conference for Supervisors, Amsterdam, April 6, 2018

Climate risks and financial risks

Risks are traversal to financial risks

- **Carbon risk** (reputational and regulation risks) $\Rightarrow$ economic, market and credit risks
- **Climate risk** (extreme weather events, natural disasters) $\Rightarrow$ economic, operational, credit and market risks

Some definitions

Climate risk

Climate Risks include transition risk and physical risks:

- Transition risk is defined as the financial risk associated with the transition to a low-carbon economy. It include policy changes, reputational impacts, and shifts in market preferences, norms and technology
- Physical risk is defined as the financial losses due to extreme weather events and climate disasters like flooding, sea level rise, wildfires, droughts and storms

Some definitions

Global warming (≈ climate change)

Global warming is the long-term heating of Earth's climate system observed since the pre-industrial period (between 1850 and 1900) due to human activities, primarily fossil fuel burning

NASA Global Climate Change — `https://climate.nasa.gov`

Some definitions

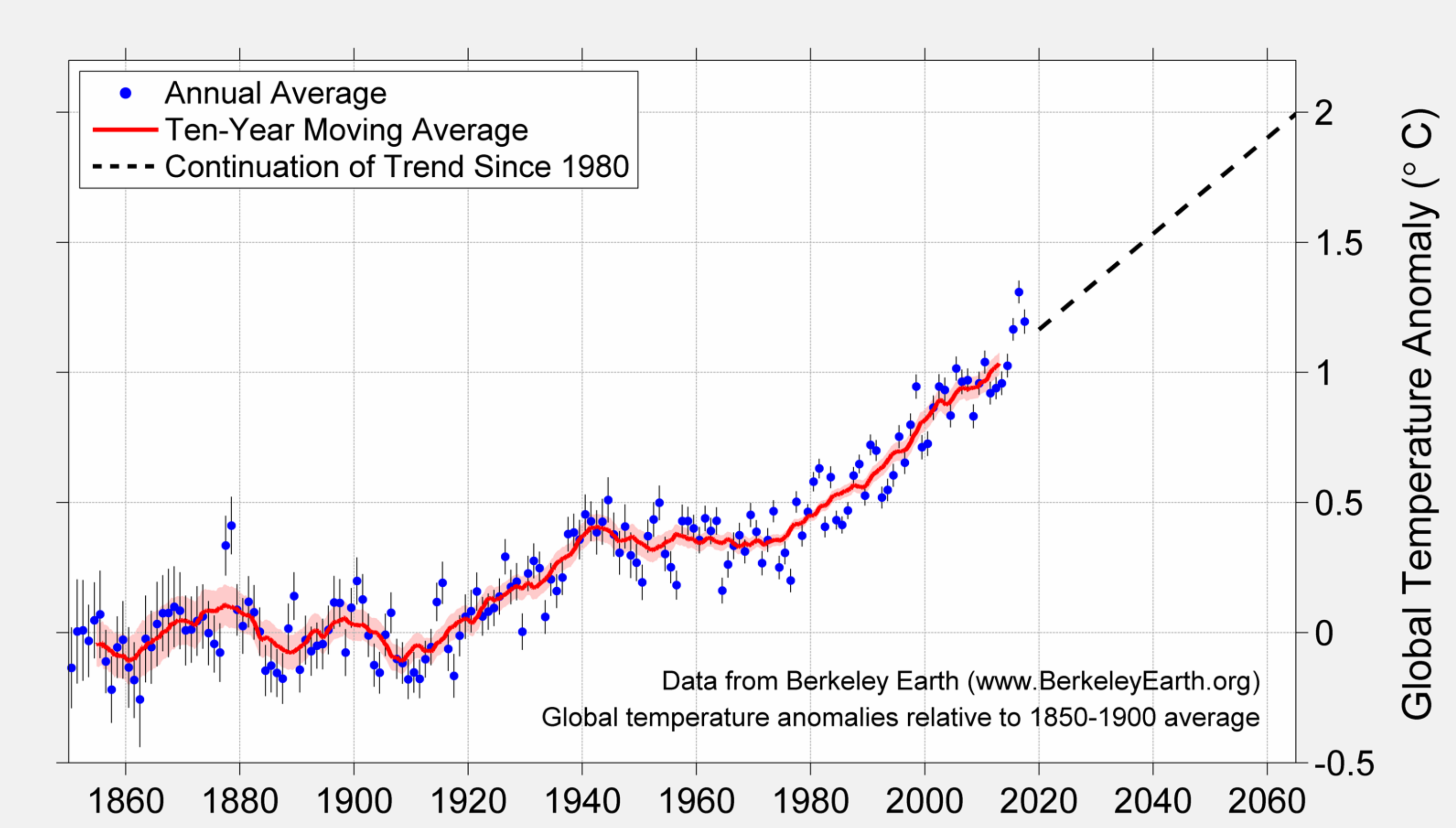


Figure 36: Global temperature anomaly

Source: Berkeley Earth (2018), `http://berkeleyearth.org`

Some definitions

Carbon risk

Carbon risks correspond to the potential financial losses due to greenhouse gas (or GHG) emissions, mainly CO_2 emissions (in a strengthening regulatory context)

Some definitions

GHG

Greenhouse gases absorb and emit radiation energy, causing the greenhouse effect[a]:

1. water vapour (H_2O)
2. Carbon dioxide (CO_2)
3. Methane (CH_4)
4. Nitrous oxide (N_2O)
5. Ozone (O_3)

[a] Without greenhouse effect, the average temperature of Earth's surface would be about -18°C. With greenhouse effect, the current temperature of Earth's surface is about $+15^\circ$C.

Some definitions

Carbon equivalent

Carbon dioxide equivalent (or CO_2e) is a term for describing different GHG in a common unit

- A quantity of GHG can be expressed as CO_2e by multiplying the amount of the GHG by its global warming potential (GWP)
- 1 kg of methane corresponds to 25 kg of CO_2
- 1 kg of Nitrous oxide corresponds to 310 kg of CO_2

CO_2 emissions

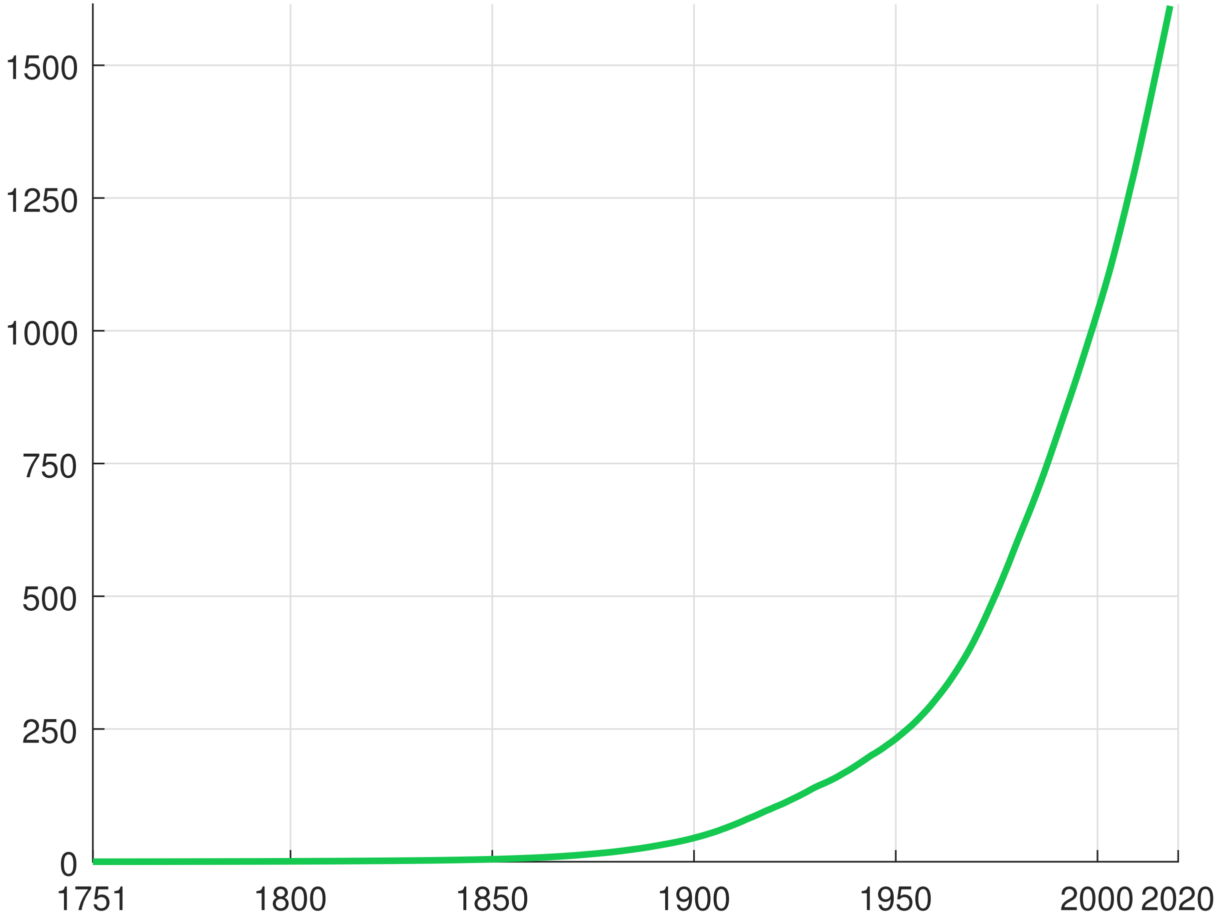


Figure 37: Cumulative CO_2 emissions (in BT)

Source: Data on CO_2 and GHG Emissions by Our World in Data (https://github.com/owid/co2-data)

CO_2 emissions

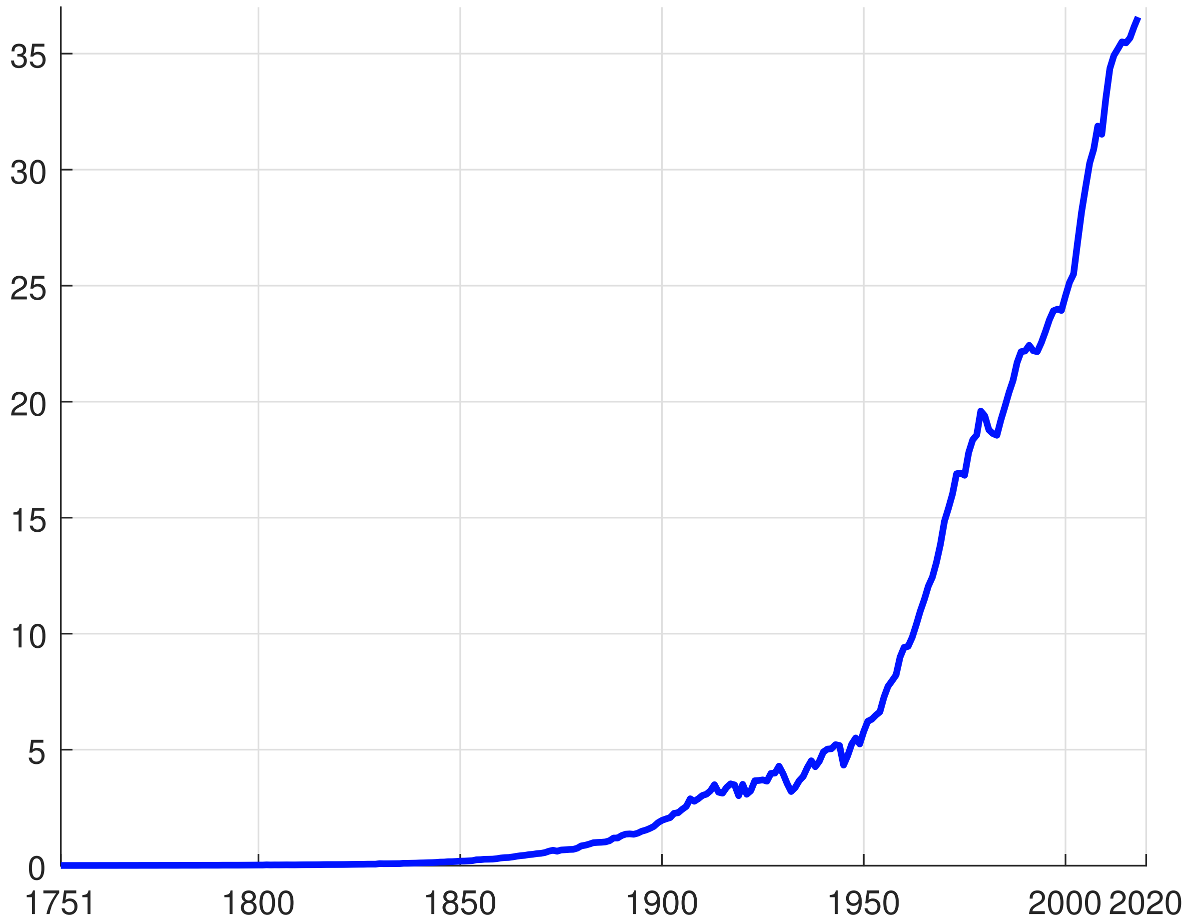


Figure 38: Annual CO_2 emissions (in BT)

Source: Data on CO_2 and GHG Emissions by Our World in Data (https://github.com/owid/co2-data)

CO_2 emissions

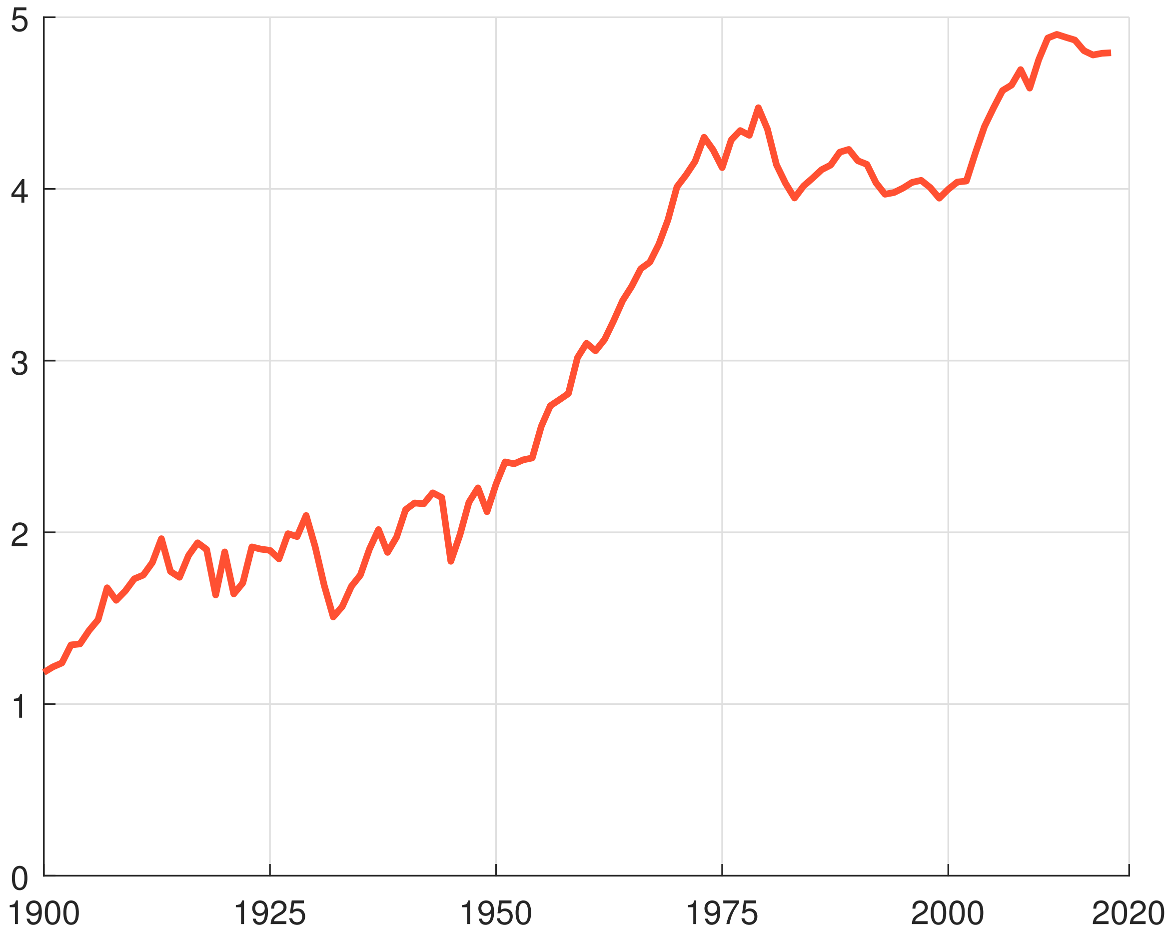


Figure 39: CO_2 emissions per capita (in MT)

Source: Data on CO_2 and GHG Emissions by Our World in Data (`https://github.com/owid/co2-data`)

CO_2 emissions

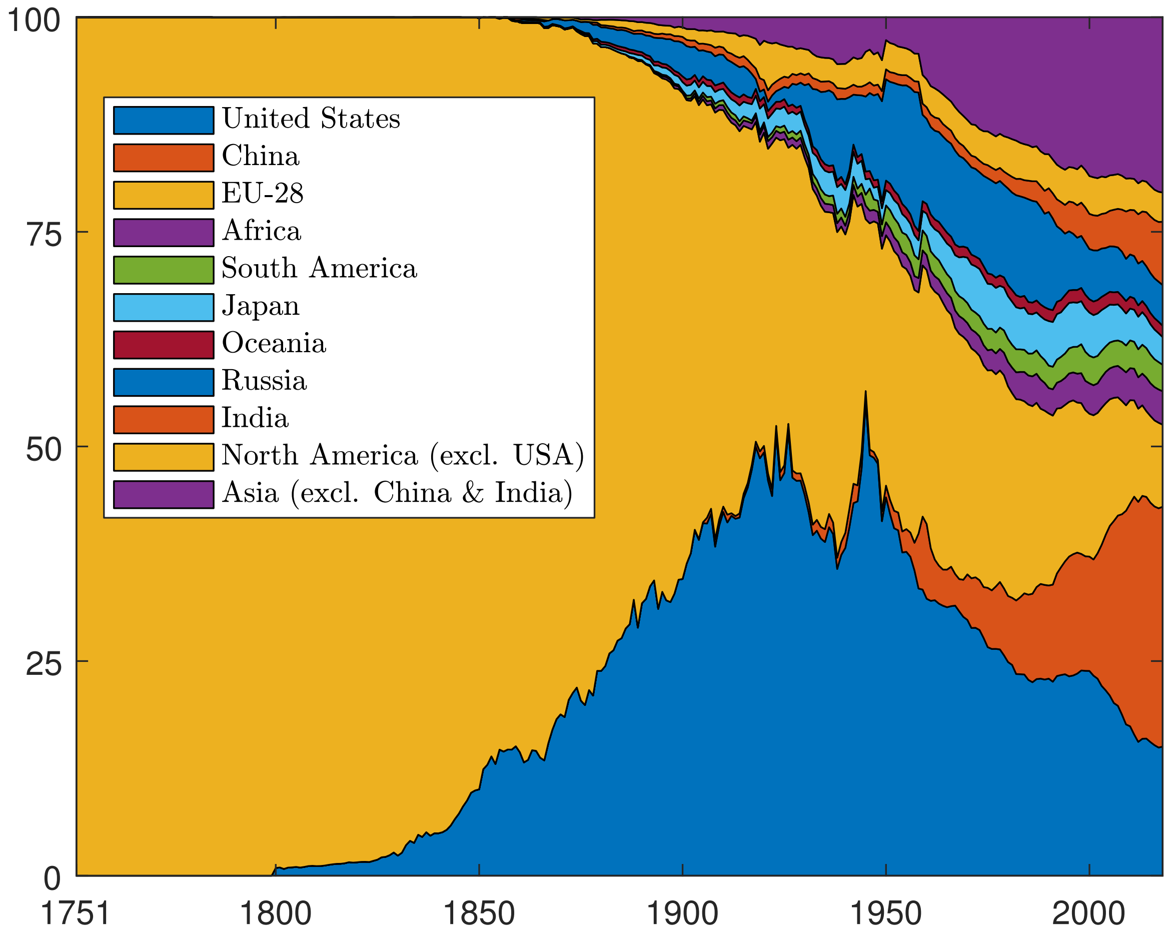
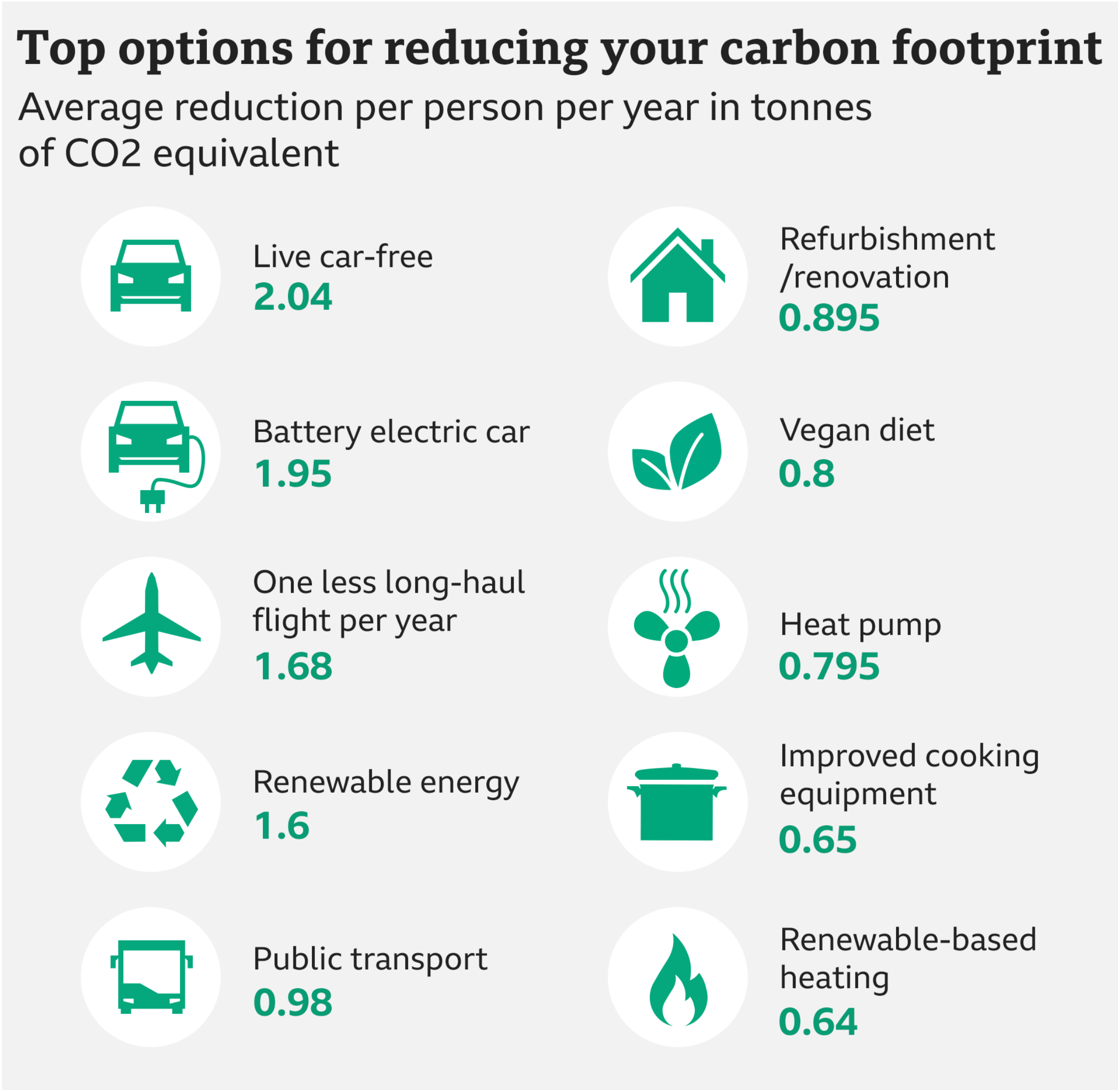


Figure 40: Share of CO_2 emissions (in %)

Source: Data on CO_2 and GHG Emissions by Our World in Data (`https://github.com/owid/co2-data`)

CO_2 emissions



Source: Centre for Research into Energy Demand Solutions BBC

IPCC

- The Intergovernmental Panel on Climate Change (IPCC) is the United Nations body for assessing the science related to climate change
- The IPCC was created to provide policymakers with regular scientific assessments on climate change, its implications and potential future risks, as well as to put forward adaptation and mitigation options
- Website: `https://www.ipcc.ch`

Remark

IPCC is known as "*Groupe d'experts intergouvernemental sur l'évolution du climat*" (GIEC)

IPCC

IPCC working groups

- The IPCC Working Group I (WGI) examines the physical science underpinning past, present, and future climate change
- The IPCC Working Group II (WGII) assesses the impacts, adaptation and vulnerabilities related to climate change
- The IPCC Working Group II (WGIII) focuses on climate change mitigation, assessing methods for reducing greenhouse gas emissions, and removing greenhouse gases from the atmosphere

IPCC

Some famous reports

- IPCC Fifth Assessment Report (AR5): Climate Change 2014 — `www.ipcc.ch/report/ar5`
- Global Warming of 1.5°C — `www.ipcc.ch/sr15`
- IPCC Sixth Assessment Report (AR6): Climate Change 2022 — `www.ipcc.ch/report/sixth-assessment-report-cycle`

IPCC scenarios

- Website: `https://www.ipcc.ch/data`
- The IPCC AR5 scenarios database comprises 31 models and in total 1 184 scenarios
- 4 reference scenarios: **representative concentration pathways** (RCP)
- Each RCP represents one possible evolution profile of GHG concentrations
  - RCP 2.6: CO_2 emissions start declining by 2020 and go to zero by 2100
  - RCP 4.5: CO_2 emissions peak around 2040, then decline
  - RCP 6.0: CO_2 emissions peak around 2080, then decline
  - RCP 8.5: CO_2 emissions continue to rise throughout the 21st century
- For each RCP, socio-economic development scenarios and various adaptation and mitigation strategies are associated
- They are called the **shared socioeconomic pathways** (SSP)

IPCC scenarios

RCP	Model	Contact
RCP 2.6	IMAGE	Detlef van Vuuren (detlef.vanvuuren@pbl.nl)
RCP 4.5	MiniCAM	Katherine Calvin (katherine.calvin@pnnl.gov)
RCP 6.0	AIM	Toshihiko Masui (masui@nies.go.jp)
RCP 8.5	MESSAGE	Keywan Riahi (riahi@iiasa.ac.at)

Table 12: Associated model for each RCP

IPCC scenarios

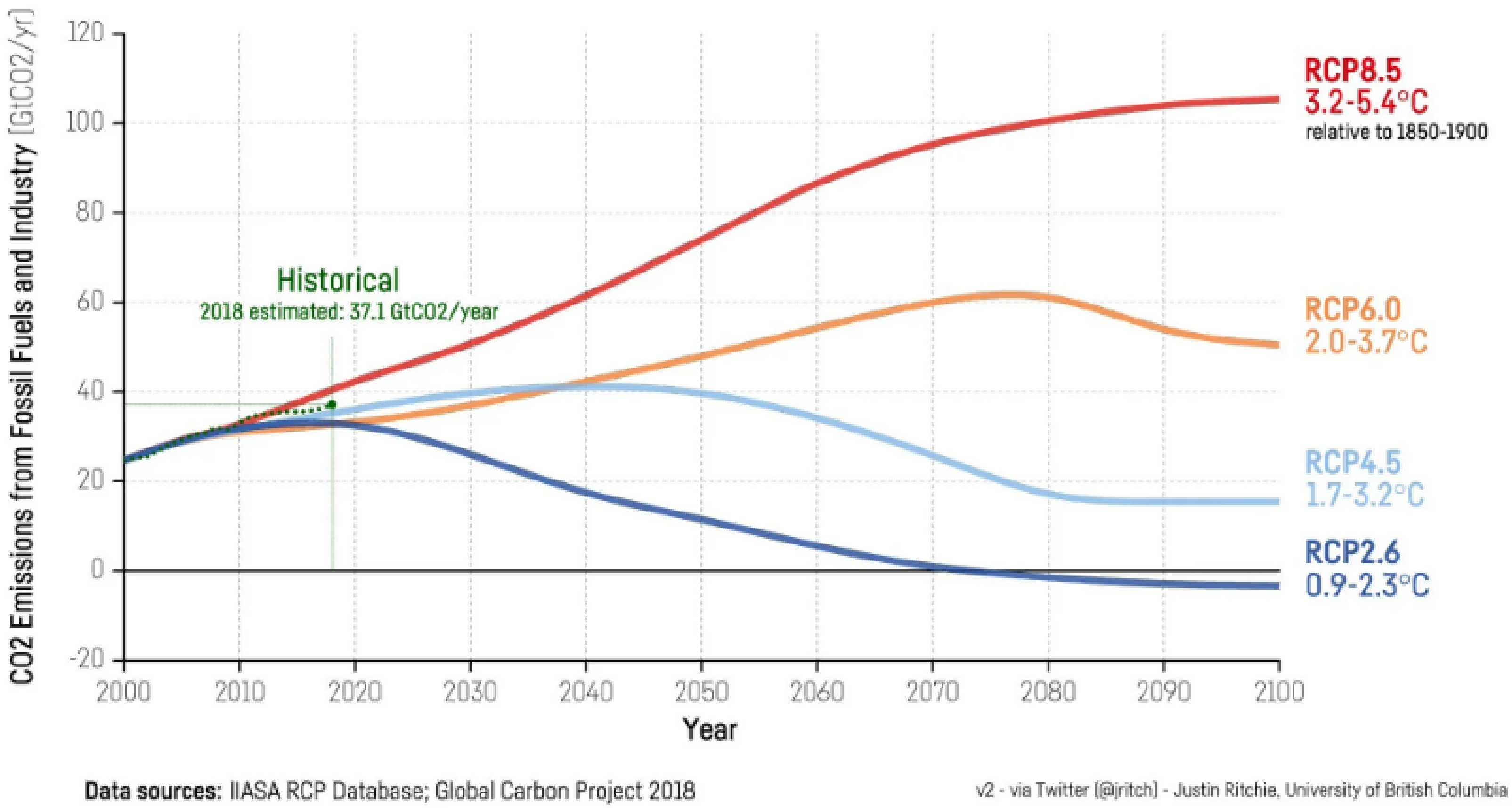


Figure 41: IPCC RCP scenarios: CO_2 emissions from fossil fuels and industry

Carbon neutrality

Carbon neutrality (or net zero) means that any CO2 released into the atmosphere from human activity is balanced by an equivalent amount being removed

Apple Commits to Become Carbon Neutral to by 2030
(`https://www.bbc.com/news/technology-53485560`)

Carbon dioxide removal

Carbon dioxide removal (CDR)

1. Nature-based solutions
   - Afforestation
   - Reforestation
   - Restoration of peat bogs
   - Restoration of coastal and marine habitats
2. Enhanced natural processes
   - Land management and no-till agriculture, which avoids carbon release through soil disturbance
   - Better wildfire management
   - Ocean fertilisation to increase its capacity to absorb CO2
3. Technology solutions
   - Bioenergy with carbon capture and storage (BECCS)
   - Direct air capture (DAC)

The shared socioeconomic pathways

SSP1	Low challenges for both mitigation and adaptation, rapid development: **Sustainability** (Taking the Green Road)
SSP2	Moderate challenges for mitigation and adaptation: **Middle of the Road**
SSP3	High challenges for both mitigation and adaptation — Concern about competitiveness, security and regional conflict pushing countries to focus on regional issues: **Regional Rivalry** (a Roacky Road)
SSP4	Low challenges for mitigation hight for adaptation — Unequal investment in human capital, concentration of power in a small business elite: **Inequality** (A Divided Road)
SSP5	High challenge for mitigation low for adaptation: **Fossil-fueled Development** (Taking the Highway)

Figure 42: The shared socioeconomic pathways

Source: O'Neill *et al.* (2016)

The shared socioeconomic pathways

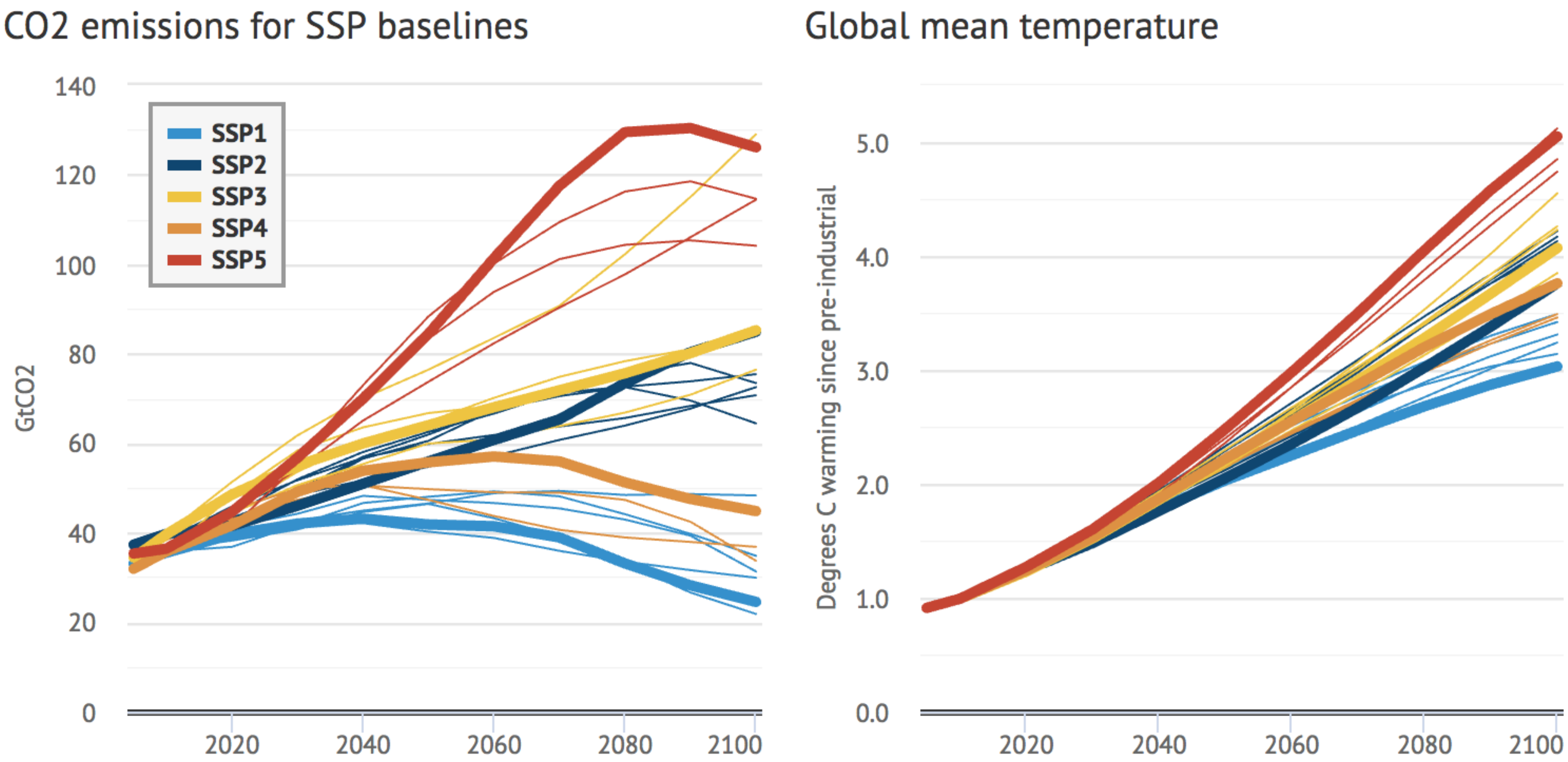


Figure 43: Projections of CO_2 emissions and temperatures across SSP

Source: https://www.carbonbrief.org/explainer-how-shared-socioeconomic-pathways-explore-future-climate-change

The shared socioeconomic pathways

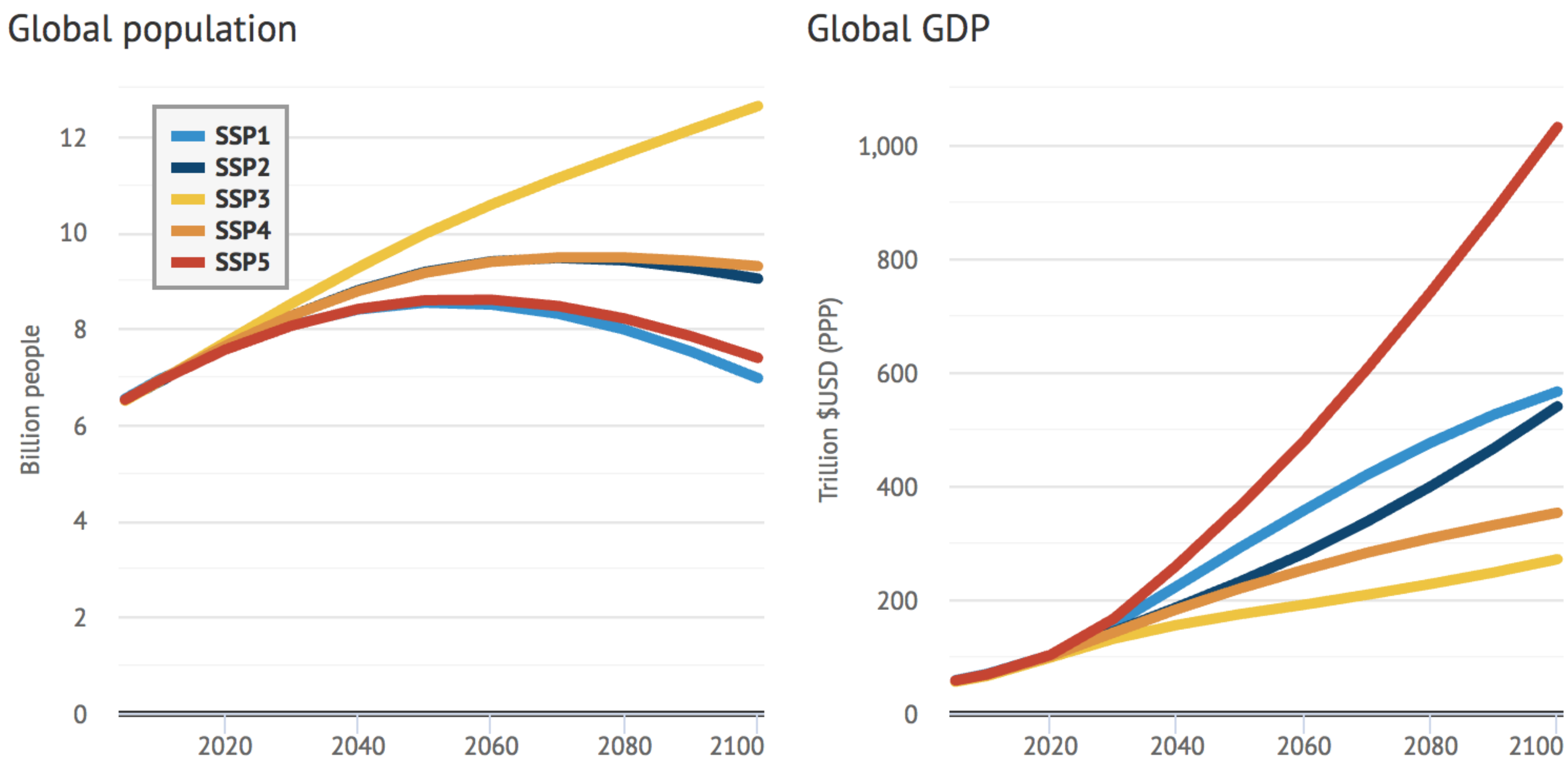


Figure 44: Projections of population and economic growth across SSP

Source: `https://www.carbonbrief.org/explainer-how-shared-socioeconomic-pathways-explore-future-climate-change`

Climate risk and missing factors

The example of permafrost

- The permafrost contains 1.700 billion tons of carbon, almost double the amount of carbon that is currently in the atmosphere.
- Arctic permafrost holds roughly 15 million gallons of mercury – at least twice the amount contained in the oceans, atmosphere and all other land combined.
- A global temperature rise of 1.5°C above current levels would be enough to start the thawing of permafrost in Siberia.
- The global warming will become out-of-control after this tipping point.
- The thawing of the permafrost also threatens to unlock disease-causing viruses long trapped in the ice.

$\Rightarrow$ The survival of Humanity becomes uncertain if the tipping point is reached

Climate risk modeling

Remark

In what follows, we use the survey and the simulations of Le Guenedal (2019)

Climate risk modeling

The Solow growth model

The model

- Production function:

$$Y(t) = F(K(t), A(t) L(t))$$

  where $K(t)$ is the capital, $L(t)$ is the labor and $A(t)$ is the knowledge factor

- Law of motion for the capital per unit of effective labor $k(t) = K(t) / (A(t) L(t))$:

$$\frac{\mathrm{d}k(t)}{\mathrm{d}t} = s\, f(k(t)) - (g_L + g_A + \delta_K)\, k(t)$$

  where s is the saving rate, δ_K is the depreciation rate of capital and g_A and g_L are the productivity and labor growth rates

Climate risk modeling

The golden rule

Golden rule with the Cobb-Douglas production and Hicks neutrality

The equilibrium to respect the '*fairness*' between generations is:

$$k^\star = \left(\frac{s}{g_L + g_A + \delta_K} \right)^{\dfrac{1}{1-\alpha}}$$

"*Each generation in a boundless golden age of natural growth will prefer the same investment ratio, which is to say the same natural growth path*" (Phelps, 1961, page 640).

"*By a golden age I shall mean a dynamic equilibrium in which output and capital grow exponentially at the same rate so that the capital-output ratio is stationary over time*" (Phelps, 1961, page 639).

Climate risk modeling

Golden rule and climate risk

What is economic growth and what is the balanced growth path?

- There is a saving rate that maximizes consumption over time and between generations ("**the fair rate to preserve future generations**")
- Economic growth corresponds to the exponential growth of capital and output to answer the needs of the growing population
- Introducing human and natural capitals add constraints and therefore **reduce growth**!

$$\text{Economic growth} \Rightarrow \left\{ \begin{array}{l} \text{productivity} \nearrow \text{ and labor } \nearrow \\ \text{maximization of } \textbf{consumption-based utility} \text{ function} \end{array} \right.$$

Climate risk modeling

Extension to natural capital

What are the effects of environmental constraints on growth?

Introducing a decreasing natural capital (Romer, 2006)

The balanced growth path $g_Y^\star$ is equal to:

$$g_Y^\star = g_L + g_A - \frac{g_L + g_A + \delta_{N_c}}{1-\alpha}\vartheta$$

where δ_{N_c} is the depreciation rate of natural capital and ϑ is the elasticity of output with respect to (normalized) natural capital $N_c(t)$

"*The static-equilibrium type of economic theory which is now so well developed is plainly inadequate for an industry in which the indefinite maintenance of a steady rate of production is a physical impossibility, and which is therefore bound to decline*" (Hotteling, 1931, page 138-139)

Accounting for environment... changes the definition of economic growth

Climate risk modeling

Inter-temporal utility functions

Preferences modeling (Ramsey model)

- ρ is the discount rate (time preference)
- $c(t)$ is the consumption per capita and u is the CRRA utility function:

$$u(c(t)) = \begin{cases} \dfrac{1}{1-\theta} c(t)^{1-\theta} & \text{if } \theta > 0, \quad \theta \neq 1 \\ \ln c(t) & \text{if } \theta = 1 \end{cases}$$

  where θ is the risk aversion parameter
- Maximization of the welfare function:

$$\int_t^\infty e^{-\rho t} u(c(t)) \, \mathrm{d}t$$

Climate risk modeling

The discounting issue

Does the golden rule of saving rates hold in a Keynesian approach with discounted maximization of consumption?

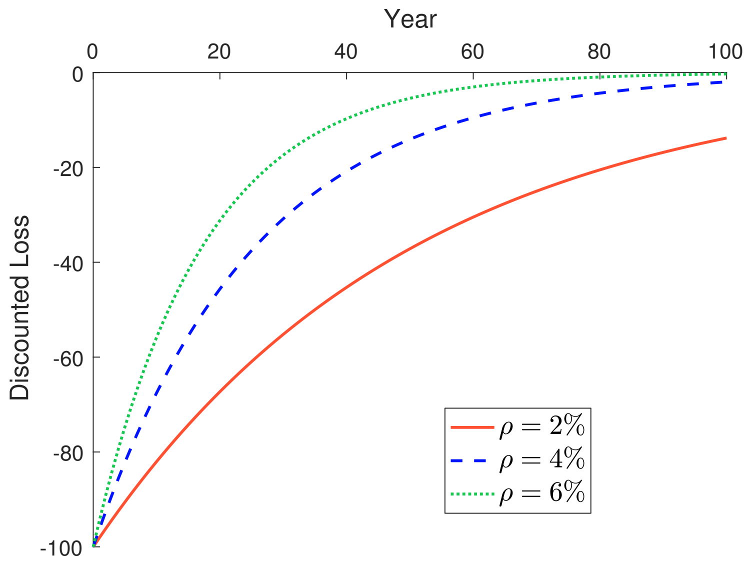


Figure 45: Discounted value of \$100 loss

- "*There is still time to avoid the worst impacts of climate change, if we take strong action now*" (Stern, 2007)
- "*I got it wrong on climate change – it's far, far worse*" (Stern, 2013)

The value of a loss in 100 years almost disappears... while it is only the next generation!

Climate risk modeling

Does consumption maximization make sense?

How many planets do we need?

To achieve the current levels of consumption for the world population, we need:

- US: 5 planets
- France: 3 planets
- India: 0.6 planet

Source: Global Footprint Network, `http://www.footprintcalculator.org`

Climate risk modeling

Fairness between generations

Keynes

"In the long run, we are all dead"

John Maynard Keynes[a], *A Tract on Monetary Reform*, 1923.

[a] *"Men will not always die quietly"*, *The Economic Consequences of the Peace*, 1919.

Carney

"The Tragedy of the Horizon"

Mark Carney, Chairman of the Financial Stability Board, 2015

$\Rightarrow$ Back to the Golden Rule and the Fable for Growthmen...

Integrated assessment model (IAM)

Definition

Main categories

- **Optimization models**
  The inputs of these models are parameters and assumptions about the structure of the relationships between variables. The outputs provided by optimization process are scenarios depending on a set of constraints
- **Evaluation models**
  Based on exogenous scenarios, the outputs provide results from partial equilibriums between variables

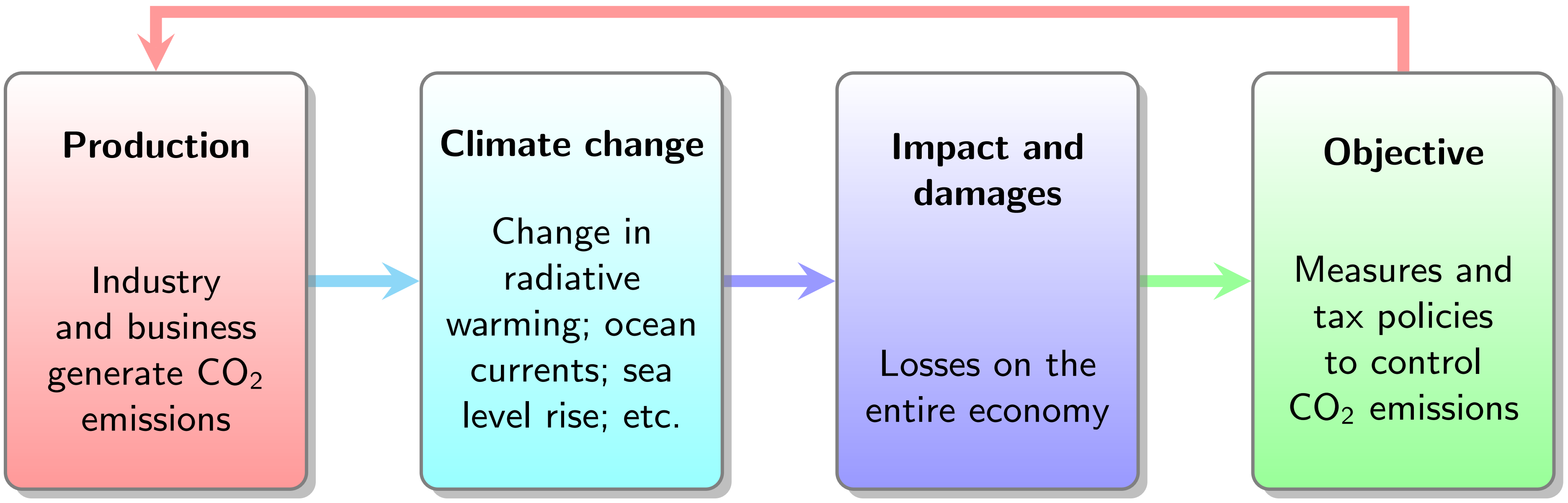
Three main components of IAMs

1. Economic growth relationships
2. Dynamics of climate emissions
3. Objective function

Integrated assessment model (IAM)

Modeling framework

Figure 46: Economic models of climate risk



Integrated assessment model (IAM)

Modeling framework

1. Economic module
    1. Production function $\Longrightarrow$ GDP
    2. Impact of the climate risk on GDP (damage losses, mitigation and adaptation costs)
    3. The climate loss function depends on the temperature
2. Climate module
    1. Dynamics of GHG emissions
    2. Modeling of Atmospheric and lower ocean temperatures
3. Optimal control problem
    1. Maximization of the utility function
    2. We can test many variants

Integrated assessment model (IAM)

Modeling framework

The most famous IAM is the **Dynamic Integrated model of Climate and the Economy** (or DICE) developed by Nordhaus[3] (1993)

The RICE model (Regional Integrated Climate-Economy model) is a variant of the DICE model

[3] 2018 Nobel Laureate

Integrated assessment model (IAM)

Production and output

- The **gross output** is equal to:

$$Y(t) = A_{\mathrm{TFP}}(t) K(t)^{\alpha} L(t)^{1-\alpha}$$

where:

$$\begin{cases} A_{\mathrm{TFP}}(t) = (1 + g_A(t)) A_{\mathrm{TFP}}(t-1) \\ K(t) = (1 - \delta_K) K(t-1) + I(t) \\ L(t) = (1 + g_L(t)) L(t-1) \end{cases}$$

- Climate change impacts the **net output**:

$$Q(t) = \Omega_{\mathrm{Climate}}(t) Y(t)$$

- We also have $Q(t) = C(t) + I(t)$ and $C(t) = (1 - s(t)) Q(t)$

Integrated assessment model (IAM)

The loss (or damage) function

- The loss function is given by:

$$\Omega_{\mathrm{Climate}}(t) = \Omega_D \cdot \Omega_\Lambda = \frac{1}{1 + D(t)} \cdot (1 - \mathit{\Lambda}(t))$$

where $D(t)$ and $\mathit{\Lambda}(t)$ measure climate damages[4] and abatement costs[5]

- Climate damages are assumed to be quadratic:

$$D(t) = a_1 \mathcal{T}_{\mathrm{AT}}(t) + a_2 \mathcal{T}_{\mathrm{AT}}(t)^2$$

where $\mathcal{T}_{AT}(t)$ is the atmospheric temperature, while abatement costs depend on the control rate $\mu(t)$:

$$\Lambda(t) = b_1 \mu(t)^{b_2}$$

[4] The climate damage coefficient $\Omega_D(t) = (1 + D(t))^{-1}$ represents the fraction of GDP lost because of the temperature increase

[5] It includes costs of reduction of greenhouse gases emission, abatement and mitigation costs

Integrated assessment model (IAM)

GHG emissions, concentrations and radiative forcing

- The total emission of green house gases $\mathcal{E}(t)$ is given by:

$$\mathcal{E}(t) = (1 - \mu(t))\,\sigma(t)\,Y(t) + \mathcal{E}_{\mathrm{Land}}(t)$$

  where mitigation policies are translated by the control rate $\mu(t)$, $\mathcal{E}_{\mathrm{Land}}(t)$ represents exogenous land-use emissions and $\sigma(t)$ is the uncontrolled ratio of green house gases emissions to output

- The evolution of the GHG concentration $\mathcal{C} = (\mathcal{C}_{\mathrm{AT}}, \mathcal{C}_{\mathrm{UP}}, \mathcal{C}_{\mathrm{LO}})$ is given by:

$$\mathcal{C}(t) = \Phi_{\mathcal{C},\Delta}\mathcal{C}(t-1) + B_{\mathcal{C},\Delta}\mathcal{E}(t)$$

- The increase of radiative forcing $\mathcal{F}_{\mathrm{RAD}}(t)$ depends on the GHG concentration in the atmosphere:

$$\mathcal{F}_{\mathrm{RAD}}(t) = \eta \ln_2\left(\frac{\mathcal{C}_{\mathrm{AT}}(t)}{\mathcal{C}_{\mathrm{AT}}(1750)}\right) + \mathcal{F}_{\mathrm{EX}}(t)$$

Integrated assessment model (IAM)

Temperatures

Atmospheric and lower ocean temperatures are given by:

$$\begin{aligned} C_{\mathrm{AT}} \frac{\mathrm{d}\mathcal{T}_{\mathrm{AT}}(t)}{\mathrm{d}t} &= \mathcal{F}_{\mathrm{RAD}}(t) - \lambda \mathcal{T}_{\mathrm{AT}}(t) - \gamma(\mathcal{T}_{\mathrm{LO}}(t) - \mathcal{T}_{\mathrm{AT}}(t)) \\ C_{\mathrm{LO}} \frac{\mathrm{d}\mathcal{T}_{\mathrm{LO}}(t)}{\mathrm{d}t} &= \gamma(\mathcal{T}_{\mathrm{LO}}(t) - \mathcal{T}_{\mathrm{AT}}(t)) \end{aligned}$$

where γ is the heat exchange coefficient and λ is the climate feedback parameter.

Integrated assessment model (IAM)

The optimal control problem

Simplified version of the DICE model (Nordhaus, 1993)

$$\{\mu^\star(t), s^\star(t)\} = \arg\max \sum_{t=0}^{T} \frac{u(c(t), L(t))}{(1+\rho)^t}$$

$$\text{s.t.} \quad \begin{cases} Y(t) = A_{\mathrm{TFP}}(t) K(t)^{\alpha} L(t)^{1-\alpha} \\ A_{\mathrm{TFP}}(t) = (1 + g_A(t)) A_{\mathrm{TFP}}(t-1) \\ K(t) = (1-\delta_K) K(t-1) + I(t) \\ L(t) = (1 + g_L(t)) L(t-1) \\ Q(t) = \Omega_{\mathrm{C\,lim\,ate}}(t) Y(t) \\ C(t) = (1 - s(t)) Q(t) \\ \mathcal{E}(t) = (1-\mu(t))\sigma(t) Y(t) + \mathcal{E}_{\mathrm{Land}}(t) \\ \mathcal{C}(t) = \Phi_{\mathcal{C},\Delta}\mathcal{C}(t-1) + B_{\mathcal{C},\Delta}\mathcal{E}(t) \\ \mathcal{F}_{\mathrm{RAD}}(t) = \eta \log_2\left(\frac{\mathcal{C}_{\mathrm{AT}}(t)}{\mathcal{C}_{\mathrm{AT}}(1750)}\right) + \mathcal{F}_{\mathrm{EX}}(t) \\ \mathcal{T}(t) = \Phi_{\mathcal{T},\Delta}\mathcal{T}(t-1) + B_{\mathcal{T},\Delta}\mathcal{F}_{\mathrm{RAD}}(t) \end{cases}$$

Integrated assessment model (IAM)

Scenario analysis

The process of building scenarios is the same in every model

1. Choice of the structure
   - Optimization or evaluation?
   - Optimization function?
   - Complexity or simplicity?
2. Calibration
   - Choice for the discount rate (Nordhaus vs Stern)
   - Calibration of energy prices and substitution (etc.)
3. Applications
   - Compare baseline scenario of the different models
   - Compute the 2°C scenario, the optimal welfare scenario, etc.

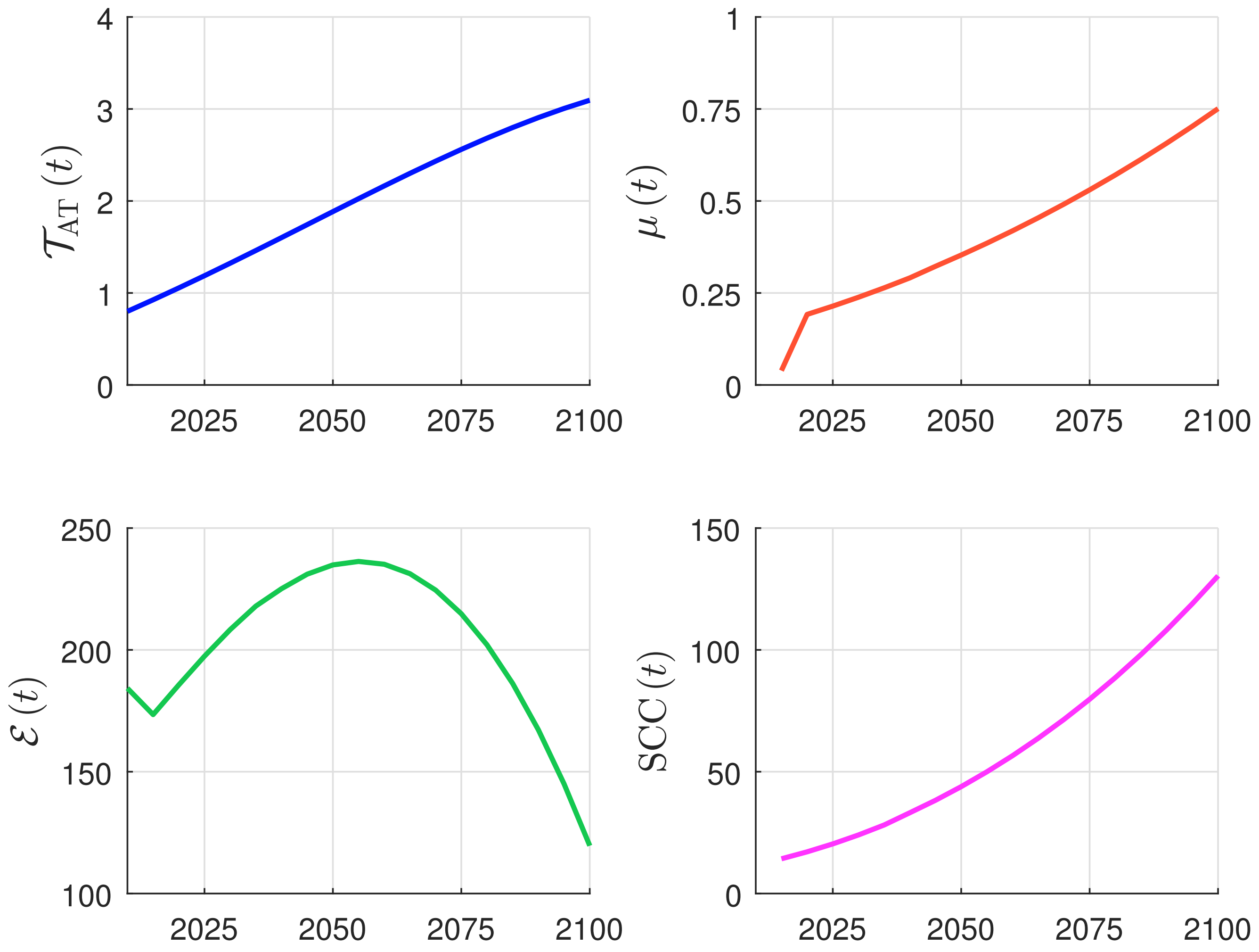
Integrated assessment model (IAM)

Important variables

- $\mathcal{T}_{\mathrm{AT}}(t)$ — Atmospheric temperature
- $\mu(t)$ — Control rate (mitigation policies)
- $\mathcal{E}(t)$ — Total emissions of GHG
- $\mathrm{SCC}(t)$ — Social cost of carbon

Integrated assessment model (IAM)

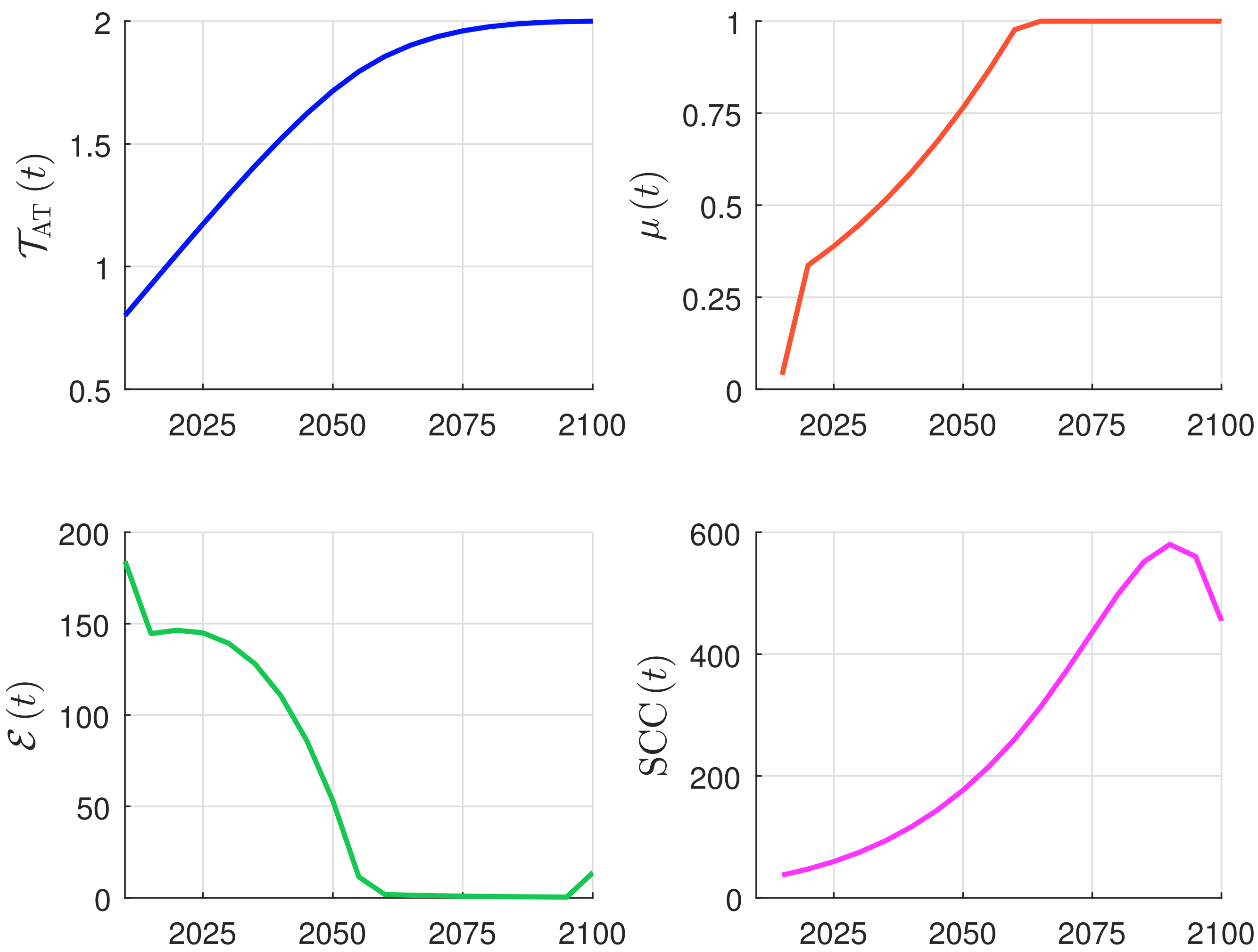
2013 DICE optimal welfare scenario



Source: Le Guenedal (2019)

Integrated assessment model (IAM)

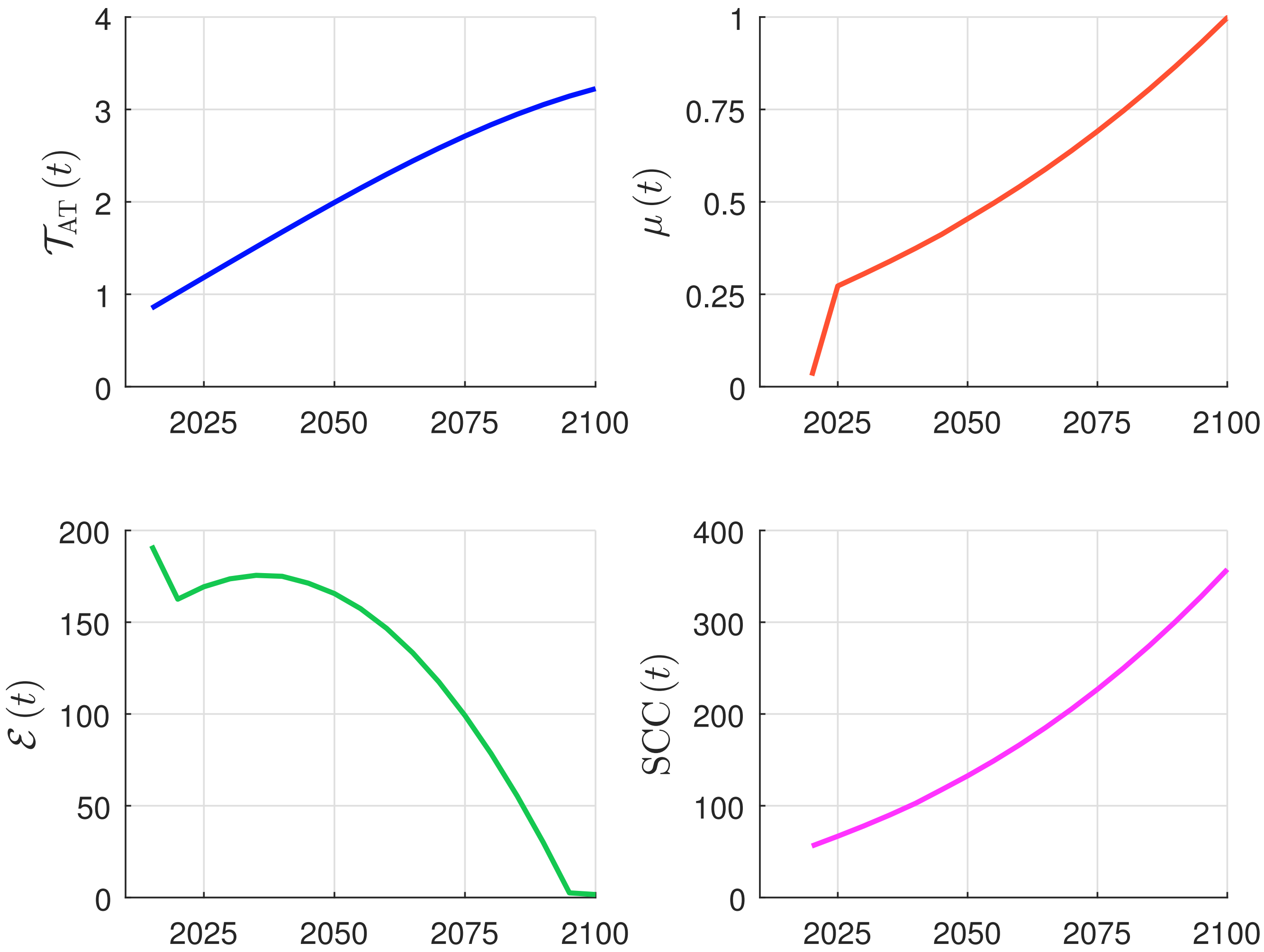
2013 DICE 2°C scenario



Source: Le Guenedal (2019)

Integrated assessment model (IAM)

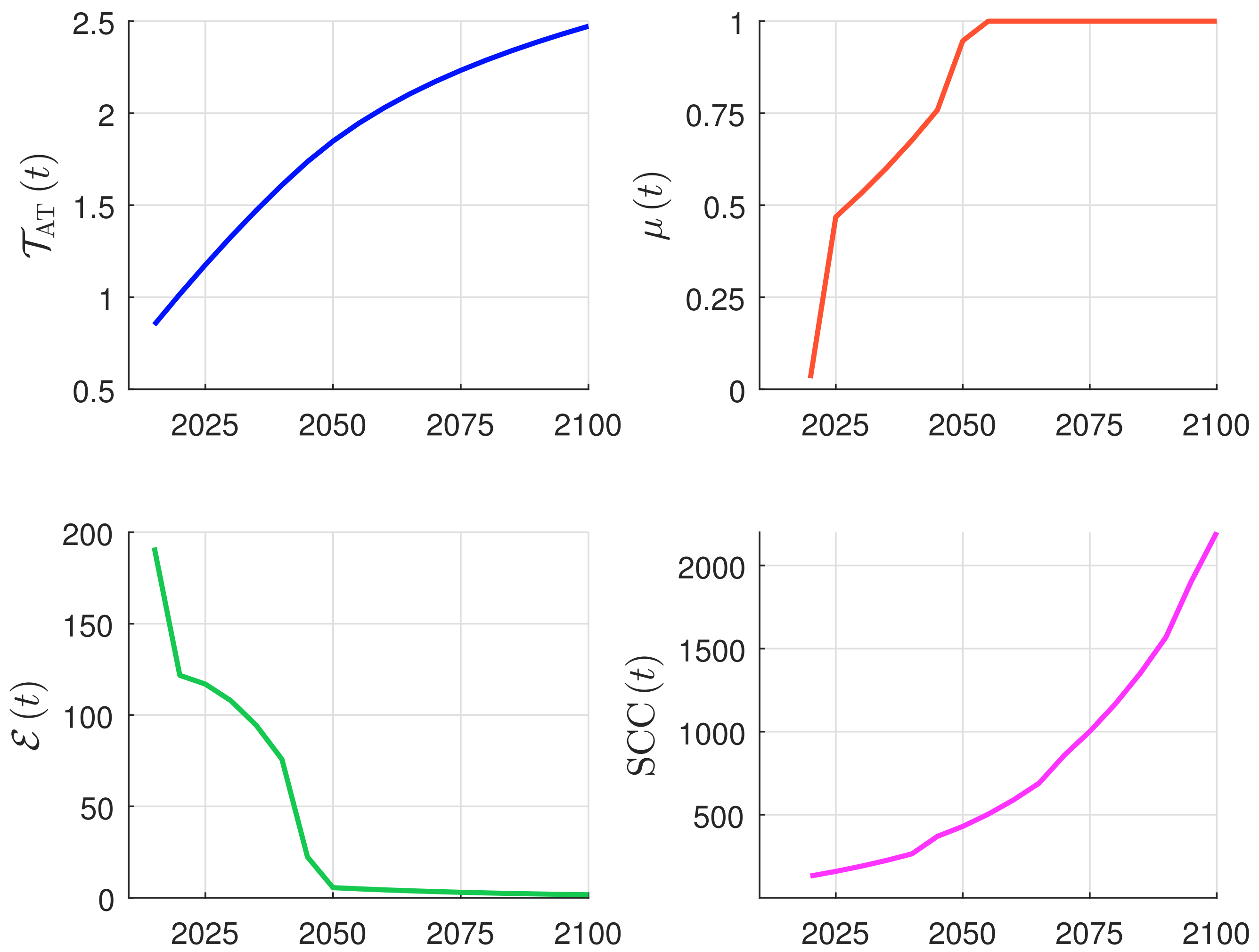
2016 DICE optimal welfare scenario



Source: Le Guenedal (2019)

Integrated assessment model (IAM)

2016 DICE 2°C scenario



Source: Le Guenedal (2019)

Integrated assessment model (IAM)

The tragedy of the horizon

Achieving the 2°C scenario

- In 2013, the DICE model suggested to reduce drastically CO_2 emissions...
- Since 2016, **the 2°C trajectory is no longer feasible!** (minimum $\approx$ 2.6°C)
- For many models, we now have:

$$\mathbb{P}\left(\Delta T > 2^{\circ} C\right) > 95\%$$

Integrated assessment model (IAM)

Malthusianism and climate risk

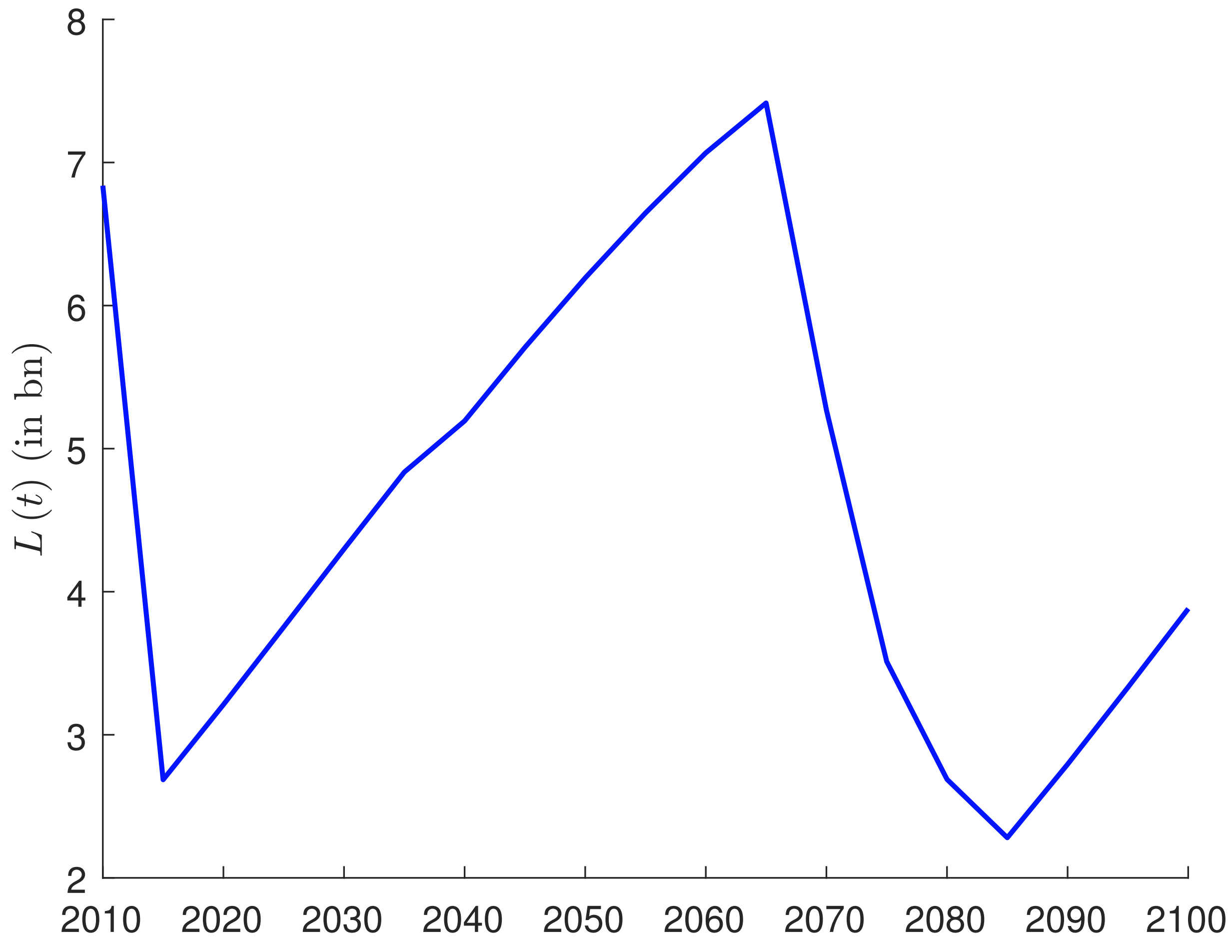


Figure 47: Optimal control on population growth rate (2°C scenario)

Integrated assessment model (IAM)

Social cost of carbon (SCC)

"This concept represents the economic cost caused by an additional ton of carbon dioxide emissions (or more succinctly carbon) or its equivalent. [...] In the language of mathematical programming, the SCC is the shadow price of carbon emissions along a reference path of output, emissions, and climate change" (Nordhaus, 2011).

Mathematical definition

We have:

$$\mathrm{SCC}(t) = \frac{\partial W^{\star} / \partial \mathcal{E}(t)}{\partial W^{\star} / \partial C(t)} = \frac{\partial C(t)}{\partial \mathcal{E}(t)}$$

Integrated assessment model (IAM)

Debate around the social cost of carbon

We have:

- \$266/tCO_2 for Stern (2007)
- \$57/tCO_2 for Golosov *et al.* (2014)
- \$31.2/tCO_2 for Nordhaus (2018) in the case of optimal welfare
- \$229/tCO_2 for Nordhaus (2018) in the case of the 2.5°C scenario
- \$125/tCO_2 for Daniel *et al.* (2018)

Integrated assessment model (IAM)

Limits of IAMs

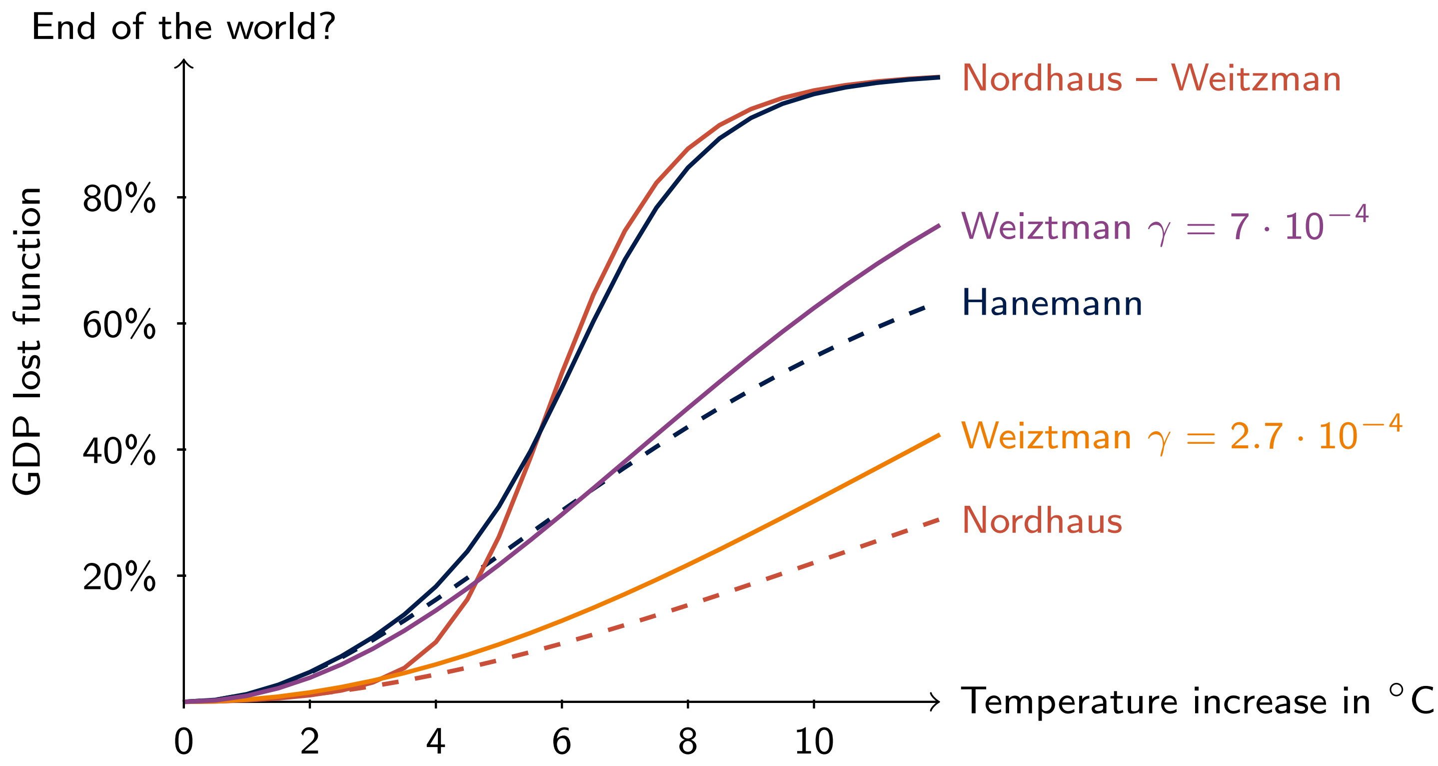


Figure 48: Damage functions

$\Rightarrow$ There is high uncertainty above 2°C and **financial models cannot be based on damage functions**

Integrated assessment model (IAM)

Limits of IAMs

- Financial models do not account for portfolio contribution to the technical change (**adaptation/mitigation**)
- The direct exposure to an **optimal tax** (regulation risk) may be approached by using optimization models of policy makers. However, each model leads to a different carbon price...
- Interconnectedness and systemic risks
- First round losses $\neq$ second round losses
- Stranded assets

Integrated assessment model (IAM)

Limits of IAMs

- AIM
- DICE/RICE
- FUND
- GCAM
- IMACLIM (CIRED)
- IMAGE
- MESSAGE
- MiniCAM
- PAGE
- REMIND
- RESPONSE (CIRED)
- WITCH

Regulation of climate risk

- UN, international bodies & coalitions
- Countries
- Cities
- Industry self-regulation
- Non-governmental organizations (NGO)
- Financial regulators

Hard regulation $\neq$ **soft regulation**

Regulation of climate risk

UN

United Nations Climate Change Conference

- Conference of the Parties (COP)
- Dealing with climate change
- COP 1: Berlin (1995)
- COP 3: Kyoto (1997) $\Rightarrow$ Kyoto Protocol (CMP)
- COP 21: Paris (2015) $\Rightarrow$ Paris Agreement (CMA)
- COP 26: Glasgow (2022)

Regulation of climate risk
UN

The **Kyoto Protocol** is an international treaty that commits state parties to reduce GHG emissions, based on the scientific consensus that:

1. **Global warming is occurring**
2. It is likely that **human-made CO_2 emissions have caused it**

Regulation of climate risk

UN

The **Paris Agreement** is an international treaty with the following goals:

1. Keep a global temperature rise this century well below 2°C above the pre-industrial levels
2. Pursue efforts to limit the temperature increase to 1.5°C
3. Increase the ability of countries to deal with the impacts of climate change
4. Make finance flows consistent with low GHG emissions and climate-resilient pathways

$\Rightarrow$ Nationally determined contributions (NDC)

Regulation of climate risk

UN

Table 13: CO_2 emissions by country

Rank	Country	CO_2 emissions Total (in GT)	Share	CO_2 emissions Per capita (in MT)
1	China	10.06	28%	7.2
2	USA	5.41	15%	15.5
3	India	2.65	7%	1.8
4	Russia	1.71	5%	12.0
5	Japan	1.16	3%	8.9
6	Germany	0.75	2%	8.8
7	Iran	0.72	2%	8.3
8	South Korea	0.72	2%	12.1
9	Saudi Arabia	0.72	2%	17.4
10	Indonesia	0.72	2%	2.2
11	Canada	0.56	2%	15.1
15	Turkey	0.42	1%	4.7
17	United Kingdom	0.37	1%	5.8
19	France	0.33	1%	4.6
17	Italy	0.33	1%	5.3

Source: Earth System Science Data, `https://earth-system-science-data.net`

World Bank Open Data, `https://data.worldbank.org/topic/climate-change`

Regulation of climate risk

UN

Paris Agreement: where we are?

- 194 states have signed the Agreement
- They represent about 80% of GHG emissions
- USA, Iran and Turkey have not signed the Agreement

Regulation of climate risk

UN

Figure 49: Paris Agreement assessments of aviation and shipping

Source: Climate Action Tracker (CAT), https://climateactiontracker.org

Regulation of climate risk
Coalitions

- **The Coalition of Finance Ministers for Climate Action**

  `www.financeministersforclimate.org`

  - Commitment to implement fully the Paris Agreement
  - Santiago Action Plan
  - Helsinki principles (1. align, 2. share, 3. promote, 4. mainstream, 5. mobilize, 6. engage)

Regulation of climate risk

Coalitions

- **One Planet Summit**

  www.oneplanetsummit.fr

- **One Planet Sovereign Wealth Funds (OPSWF)**
  - Funding members: Abu Dhabi Investment Authority (ADIA), Kuwait Investment Authority (KIA), NZ Superannuation Fund (NZSF), Public Invesment Fund (PIF), Qatar Investment Authority (QIA)
  - New members: Bpifrance, CDP Equity, COFIDES, FONSIS, ISIF, KIC, Mubadala IC, NIIF, NIC NBK
- **One Planet Asset Managers**
  - Funding members: Amundi AM, BlackRock, BNP PAM, GSAM, HSBC Global AM, Natixis IM, Northern Trust AM, SSGA
  - New members: AXA IM, Invesco, Legal & General IM, Morgan Stanley IM, PIMCO UBS AM
- **One Planet Private Equity Funds**
  - Members: Ardian, Carlyle Group, Global Infrastructure Partners, Macquarie Infrastructure and Real Assets (MIRA), SoftBank IA

Regulation of climate risk
Countries

The example of France

- August 2015: French Energy Transition for Green Growth Law (or Energy Transition Law)
- Roadmap to mitigate climate change and diversify the energy mix

Regulation of climate risk

Countries

Article 173 of the French Energy Transition Law

- The annual report of listed companies must include:
  - Financial risks related to the effects of climate change
  - The measures adopted by the company to reduce them
  - The consequences of climate change on the company's activities
- New requirements for investors:
  - Disclosure of climate (and ESG) criteria into investment decision making process
  - Disclosure of the contribution to the energy transition and the global warming limitation international objective
  - Reporting on climate change-related risks (including both physical risks and transition risks), and GHG emissions of assets
- Banks and credit providers shall conduct climate stress testing

Regulation of climate risk

Carbon pricing

- Polluter pays principle
  - A carbon price is a cost applied to carbon pollution to encourage polluters to reduce the amount of GHG they emit into the atmosphere
  - Negative externality

- Two instruments of carbon pricing
  1. **Carbon tax**
  2. **Cap-and-trade** (CAT) or emissions trading scheme (ETS)

- Some examples
  1. EU emissions trading system (2005) — `https://ec.europa.eu/clima/policies/ets_en`
  2. New Zealand ETS (2008)
  3. Chinese national carbon trading scheme (2017)

Regulation of climate risk
Carbon pricing

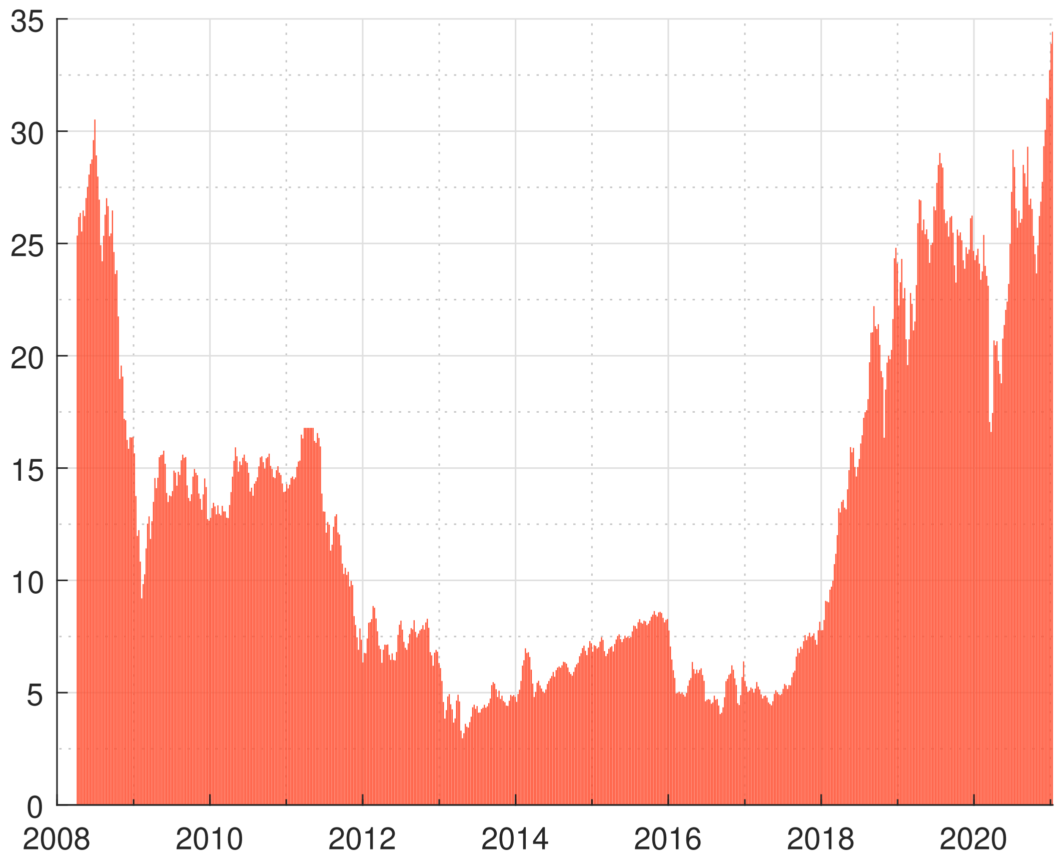


Figure 50: EU ETS carbon price* (in €/tCO_2)

(*)The carbon price reaches 34.43 euros a tonne on Monday 11, 2021

Regulation of climate risk

Carbon pricing

Table 14: Carbon tax (in \$/tCO_2)

Country	2018	2019	2020	Country	2018	2019	2020
Sweden	139.11	126.78	133.26	Latvia	5.58	5.06	10.49
Liechtenstein	100.90	96.46	105.69	South Africa			7.38
Switzerland	100.90	96.46	104.65	France	55.30	50.11	6.98
Finland	76.87	69.66	72.24	Argentina		6.24	5.94
Norway	64.29	59.22	57.14	Chile	5.00	5.00	5.00
Ireland	24.80	22.47	30.30	Colombia	5.67	5.17	4.45
Iceland	35.71	31.34	30.01	Singapore		3.69	3.66
Denmark	28.82	26.39	27.70	Mexico	3.01	2.99	2.79
Portugal	8.49	14.31	27.52	Japan	2.74	2.60	2.76
United Kingdom	25.46	23.59	23.23	Estonia	2.48	2.25	2.33
Slovenia	21.45	19.44	20.16	Ukraine	0.02	0.37	0.35
Spain	24.80	16.85	17.48	Poland	0.09	0.08	0.08

Source: World Bank Carbon Pricing Dashboard, https://carbonpricingdashboard.worldbank.org

Regulation of climate risk

Stranded assets

- Stranded Assets are assets that have suffered from unanticipated or premature write-downs, devaluations or conversion to liabilities
- For example, a 2°C alignment implies to keep a large proportion of existing fossil fuel reserves in the ground (30% of oil reserves, 50% of gas reserves and 80% of coal)
- Risk factors: Regulations, carbon prices, change in demand, social pressure, etc.
- Example of the covid-19 crisis $\Rightarrow$ air travel

Regulation of climate risk

Financial regulation

- Financial Stability Board (FSB)
- European Central Bank (ECB)
- The French Prudential Supervision and Resolution Authority (ACPR)
- The Prudential Regulation Authority (PRA)
- Network for Greening the Financial System (NGFS)
- Etc.

Regulation of climate risk

Financial regulation

Bolton, P., Despres, M., Pereira Da Silva, L.A., Samama, F. and Svartzman, R. (2020), *The Green Swan — Central Banking and Financial Stability in the Age of Climate Change*, BIS Publication, `https://www.bis.org/publ/othp31.htm`

Regulation of climate risk

Financial regulation

Task Force on Climate-related Financial Disclosures (TCFD)

- Established by the FSB in 2015 to develop a set of voluntary, consistent disclosure recommendations for use by companies in providing information to investors, lenders and insurance underwriters about their climate-related financial risks
- Website: `www.fsb-tcfd.org`
- Chairman: Michael R. Bloomberg (founder of Bloomberg L.P.)
- 31 members
- June 2017: Publication of the "*Recommendations of the Task Force on Climate-related Financial Disclosures*"
- October 2020: Publication of the 2020 "*Status Report: Task Force on Climate-related Financial Disclosures*"

Regulation of climate risk

Financial regulation

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

Table 15: The 11 recommended disclosures (TCFD, 2017)

Regulation of climate risk

Financial regulation

Some key findings of the 2020 Status Report (TCFD, 2020):

- Disclosure of climate-related financial information has increased since 2017, but continuing progress is needed
- Average level of disclosure across the Task Force's 11 recommended disclosures was 40% for energy companies and 30% for materials and buildings companies
- Asset manager and asset owner reporting to their clients and beneficiaries, respectively, is likely insufficient

Climate stress testing

- ACPR (2020): Climate Risk Analysis and Supervision[6]
- Bank of England (2021): Climate Biennial Exploratory Scenario (June 2021)

Top-down approach $\neq$ bottom-up approach

Stress of risk-weighted asset: Bouchet and Le Guenedal (2020).

[6] https://acpr.banque-france.fr/en/scenarios-and-main-assumptions-acpr-pilot-climate-exercise

Climate capital requirements

Green supporting factor

- Risk weights may depend on the green/brown nature of the credit
- Green loans
- Green supporting factor $\neq$ Brown penalising factor

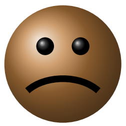
Similar idea: Green Quantitative Easing (GQE)

Climate risk measurement

- Climate risk = risk factor for long-term investors, because of its impacts on asset prices
- Managing climate risk in a portfolio first requires to measure it

Physical risk

- More an operational risk than a business risk
- Measuring physical risk is a difficult task
- Strong impact on real estate & insurance sectors
- Low impact on stock prices?



Transition risk

- A business risk
- Measuring transition risk is a difficult task
- Impact on many sectors (energy, materials, industrials, utilities, etc.)
- High impact on stock prices?

Climate risk measurement

Physical risk and tropical cyclone damage modeling

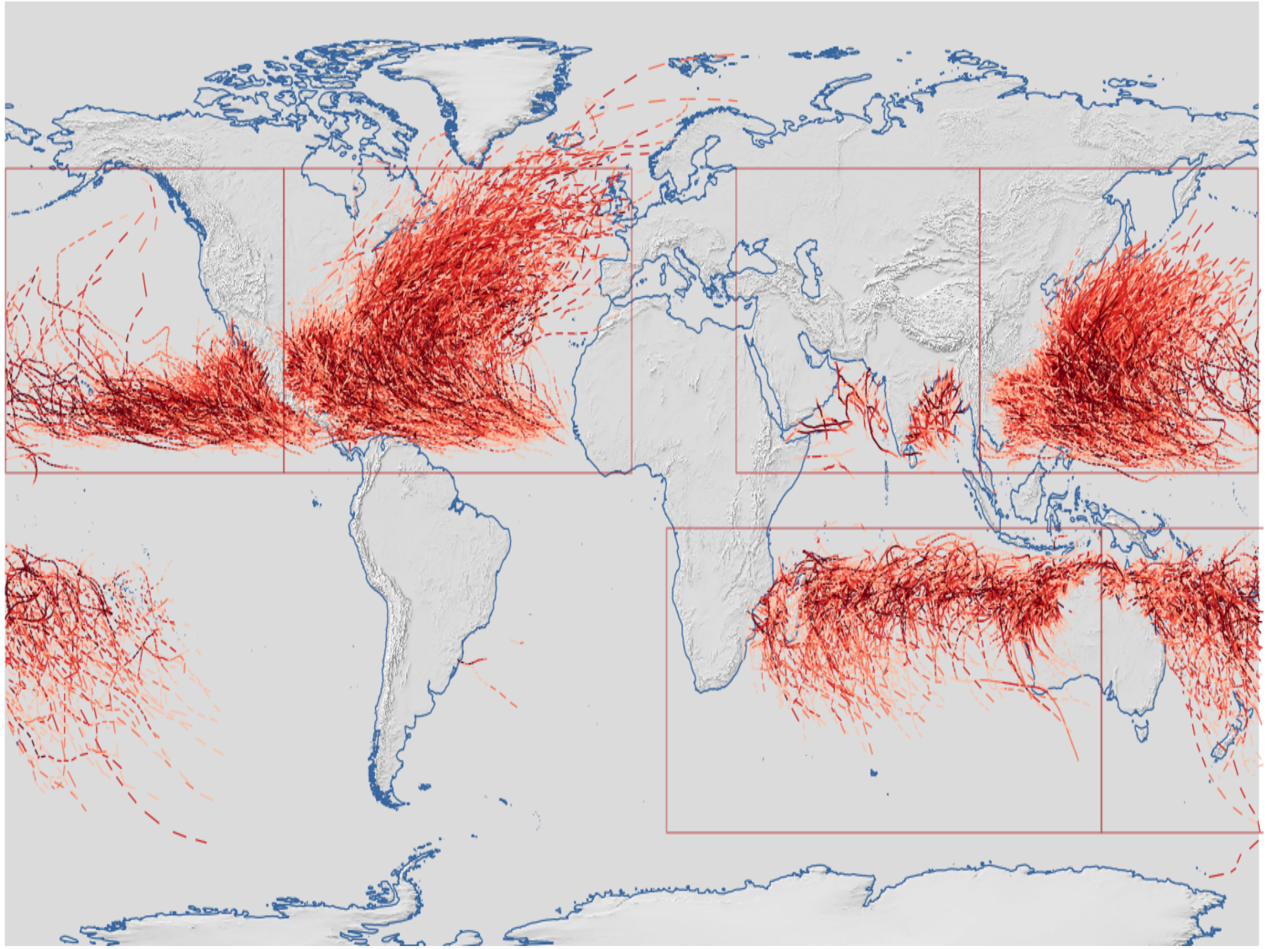


Figure 51: Sample of storms (ERA-5 climate data)

Climate risk measurement
Physical risk and tropical cyclone damage modeling

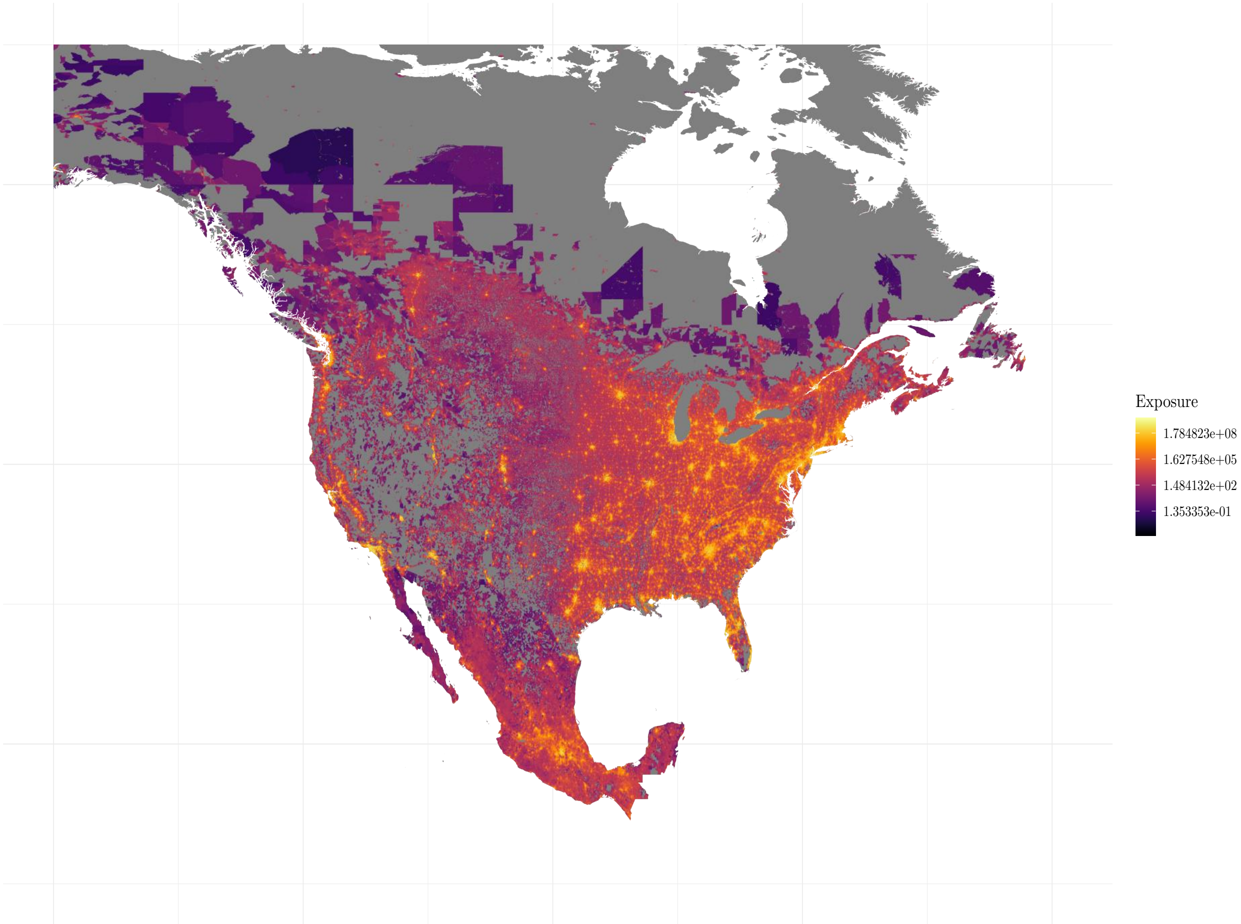
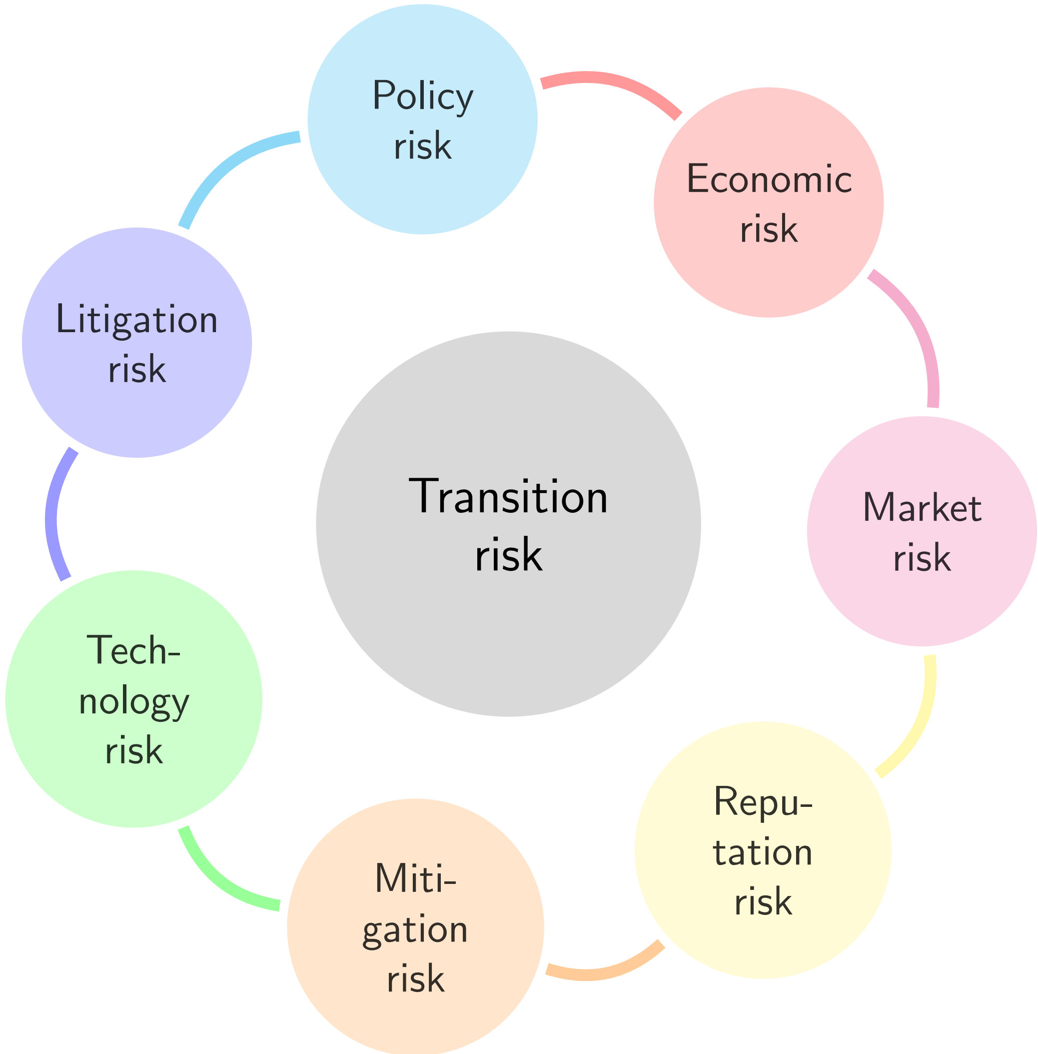


Figure 52: GDP decomposition of North America (or physical asset values) (Litpop database)

Climate risk measurement
Transition risk

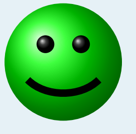


Carbon risk measurement

Main assumption

Transition risk can be measured (or approximated) by carbon risk

Carbon risk can be measured by **current** carbon emissions



Carbon risk measurement

The GHG Protocol corporate standard classifies a company's greenhouse gas emissions in three scopes:

- **Scope 1**: direct GHG emissions from all direct GHG emissions by the company
- **Scope 2**: indirect GHG emissions from the consumption of purchased energy (electricity, heat, steam, etc.)
- **Scope 3**: other indirect GHG emissions (not included in Scope 2) that occur in the value chain of the reporting company, including both upstream and downstream emissions (extraction and production of purchased materials and fuels, transport-related activities in vehicles not owned or controlled by the reporting entity, electricity-related activities not covered in Scope 2, outsourced activities, waste disposal, etc.)

Carbon risk measurement

Remark

Scopes 1 and 2 are mandatory to report, whereas scope 3 is voluntary (and harder to measure and monitor)

Carbon risk measurement

- **Carbon intensity** is the amount of GHG emissions per unit of another variable such as gross domestic product (sovereign) or revenue (corporate):

$$\text{Carbon intensity} = \frac{\text{Carbon scope}}{\text{Revenue}}$$

- Carbon scopes are measured in tCO_2e
- Carbon intensities are measured in $tCO_2e/\$$ (or $tCO_2e/\$$ mn)

Carbon footprint $\approx$ Carbon scope

Carbon footprint $\approx$ Carbon intensity

Carbon risk measurement

How to find data of carbon emission and intensity?

- **Carbon Disclosure Project (CDP)** is a not-for-profit charity that runs the global disclosure system for investors, companies, cities, states and regions to manage their environmental impacts
  `https://www.cdp.net`
- **Trucost** was established to provide the data, tools and insights needed by companies, investors and policy makers to deliver the transition to a low carbon, resource efficient economy[7]
  `https://www.trucost.com`
- ESG rating agencies: ISS ESG, MSCI, Sustainalytics, Thomson Reuters, etc.

[7] Trucost is now part of S&P Global

Carbon risk measurement

Table 16: Some carbon variables of the Trucost database

Company	Carbon-Direct[1]
Financial Year	Carbon-First Tier Indirect[1]
Trucost Sector Name	Carbon-Direct + First Tier Indirect[1]
Trucost Sector	Carbon Intensity-Direct[2]
Country	Carbon Intensity-First Tier Indirect[2]
Carbon-Scope 1[1]	Carbon Intensity-Direct + First Tier Indirect[2]
Carbon-Scope 2[1]	GHG-Direct ($ mn)
Carbon-Scope 3[1]	GHG-Indirect ($ mn)
Carbon Intensity-Scope 1[2]	GHG-Total ($ mn)
Carbon Intensity-Scope 2[2]	GHG-Direct Impact Ratio (%)
Carbon Intensity-Scope 3[2]	GHG-Indirect Impact Ratio (%)
Carbon Disclosure	GHG-Total Impact Ratio (%)
Carbon-Weighted Disclosure (%)	Revenue ($ mn)

Source: Trucost Database (2021).

(1) in t CO_2e

(1) in t CO_2e/$ mn

Carbon risk measurement

Table 17: Examples of carbon data (2019)

Company	Carbon emissions (tCO_2e)			Carbon Intensity (tCO_2e/$ mn)			Carbon
	Scope 1	Scope 2	Scope 3	Scope 1	Scope 2	Scope 3	Disclosure
Apple Inc.	50 463	862 127	27 618 943	0.194	3.314	106.156	CDP
Microsoft Corporation	113 414	3 556 553	5 977 488	0.901	28.262	47.500	CDP
Danone SA	722 122	944 877	28 969 780	25.509	33.378	1 023.365	CDP
Nestle SA	3 291 303	3 206 495	61 262 078	35.332	34.422	657.647	CDP
Sanofi	559 422	417 689	3 470 724	13.833	10.328	85.819	CDP
Pfizer Inc.	715 631	762 286	4 669 554	13.829	14.730	90.233	CDP
LVMH-Moet Vuitton	67 613	262 609	11 853 749	1.125	4.371	197.291	CDP
L'Oreal	49 511	160 393	5 556 670	1.480	4.796	166.154	CDP
BP p.l.c.	49 199 999	5 200 000	103 840 194	177.714	18.783	375.077	Env./CSR
TOTAL SE	40 909 129	3 596 127	49 893 263	204.097	17.941	248.920	CDP
Tesla Inc.	327 159	273 116	6 471 521	13.311	11.112	263.305	Estimated
Volkswagen AG	4 494 066	5 973 894	65 335 372	15.890	21.123	231.016	CDP

Source: Trucost Database (2021).

In 2019, there are 12 989 companies in the Trucost data.

Carbon risk measurement

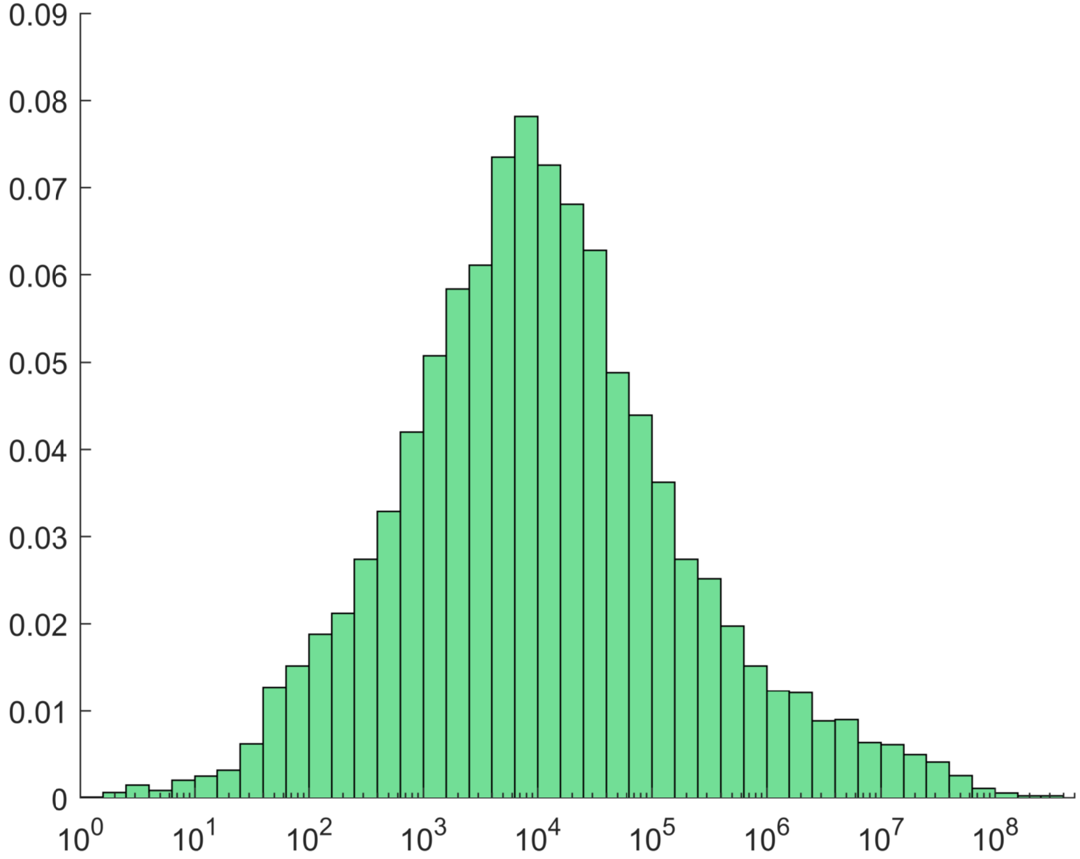


Figure 53: Histogram of carbon emissions (Scope 1, tCO_2e)

Source: Trucost Database (2021) & author's calculations.

Carbon risk measurement

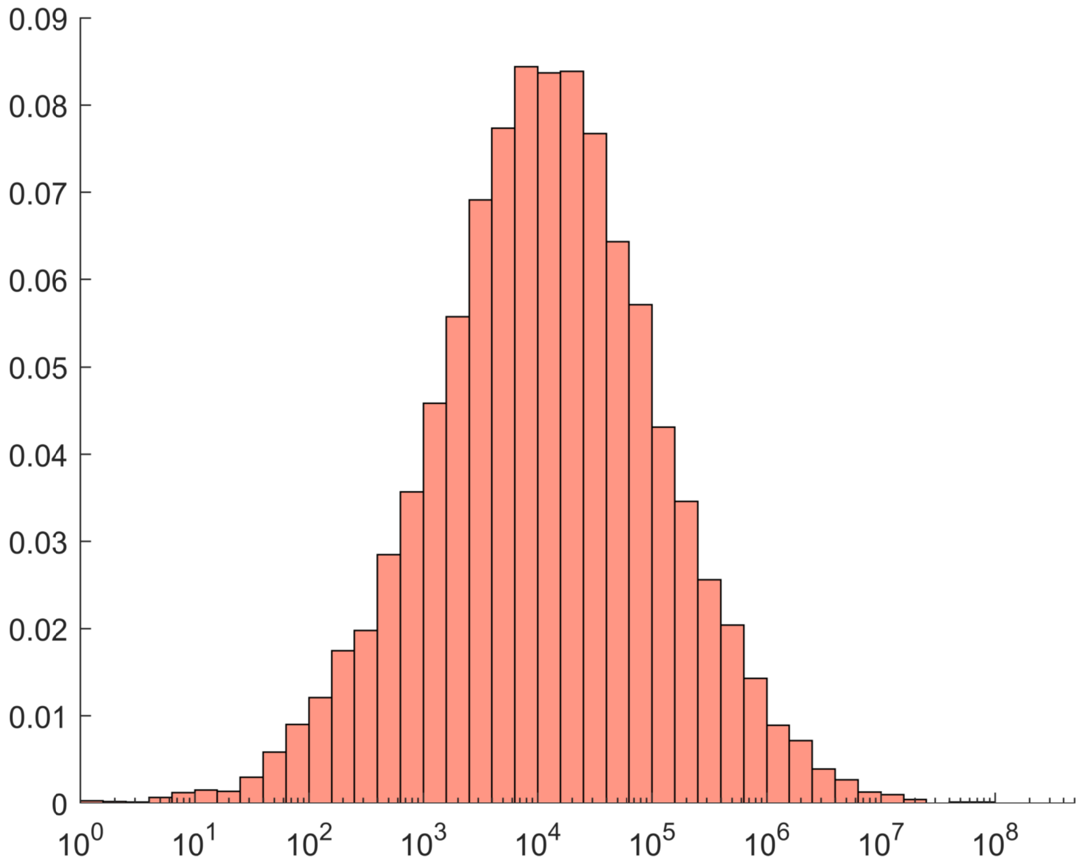


Figure 54: Histogram of carbon emissions (Scope 2, tCO_2e)

Source: Trucost Database (2021) & author's calculations.

Carbon risk measurement

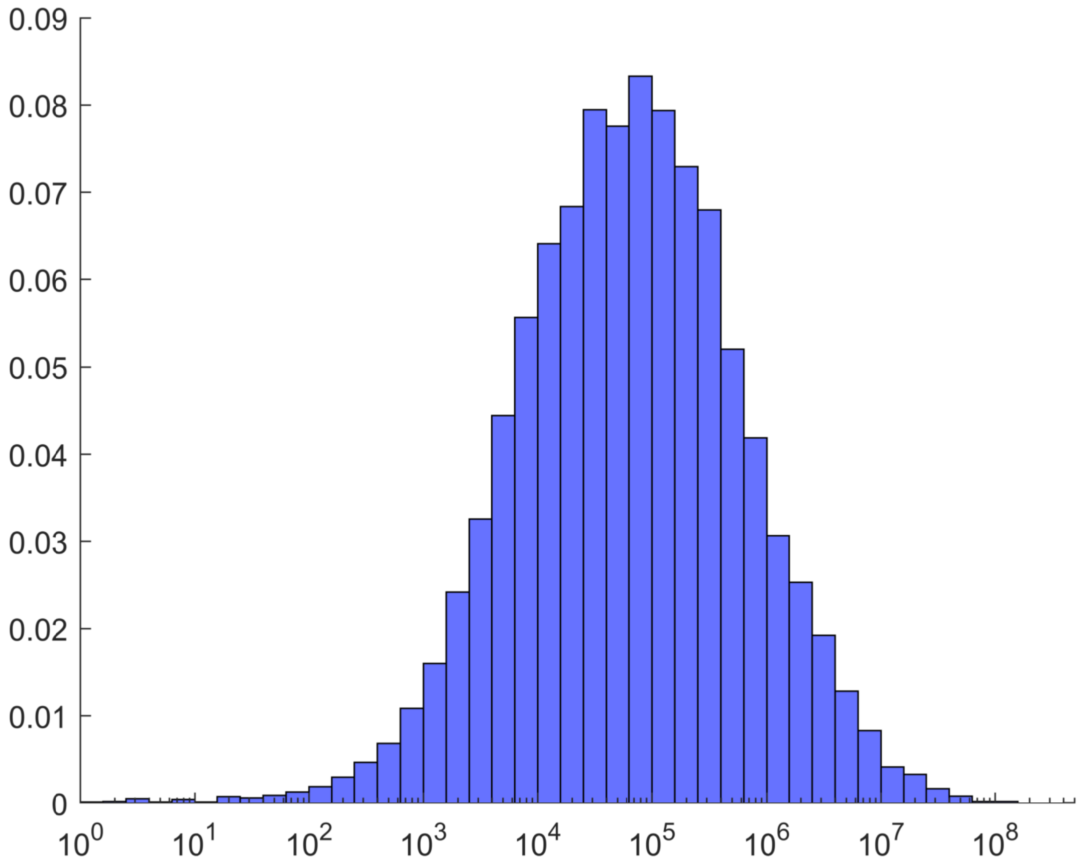


Figure 55: Histogram of carbon emissions (Scope 3, tCO_2e)

Source: Trucost Database (2021) & author's calculations.

Carbon risk measurement

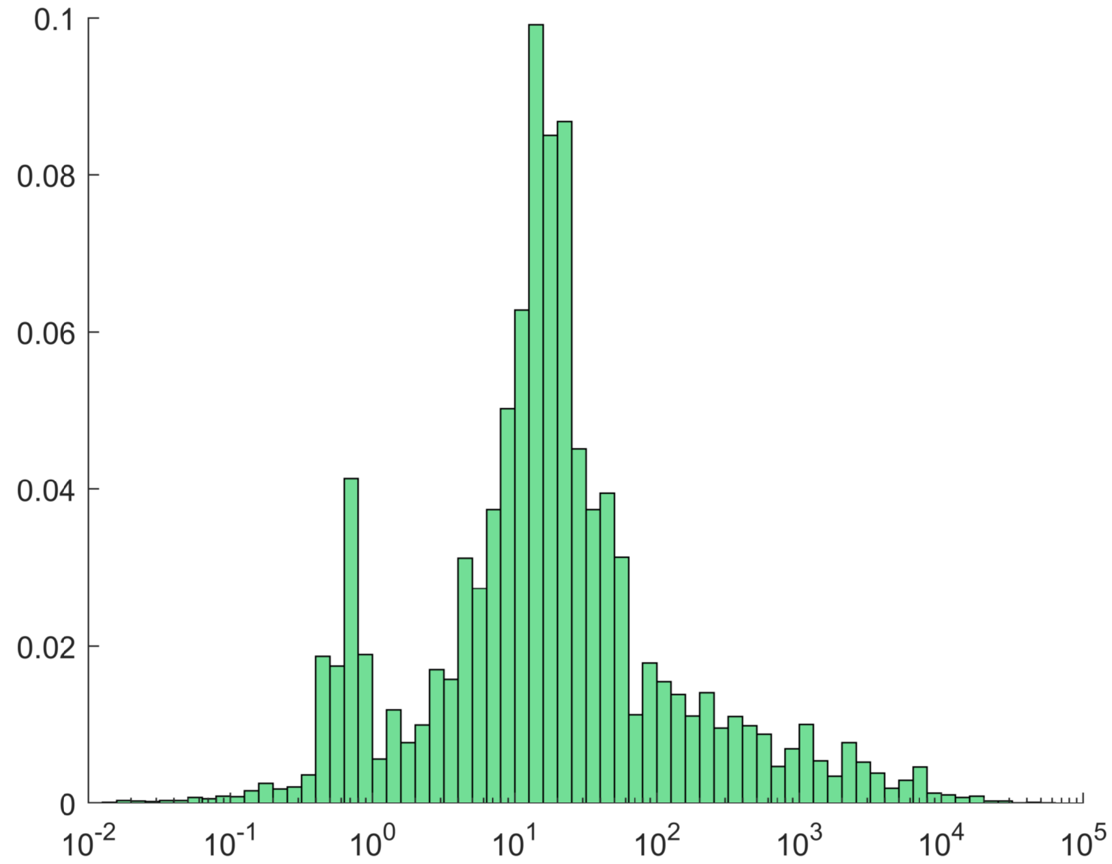


Figure 56: Histogram of carbon intensity (Scope 1, tCO_2e/\$ mn)

Source: Trucost Database (2021) & author's calculations.

Carbon risk measurement

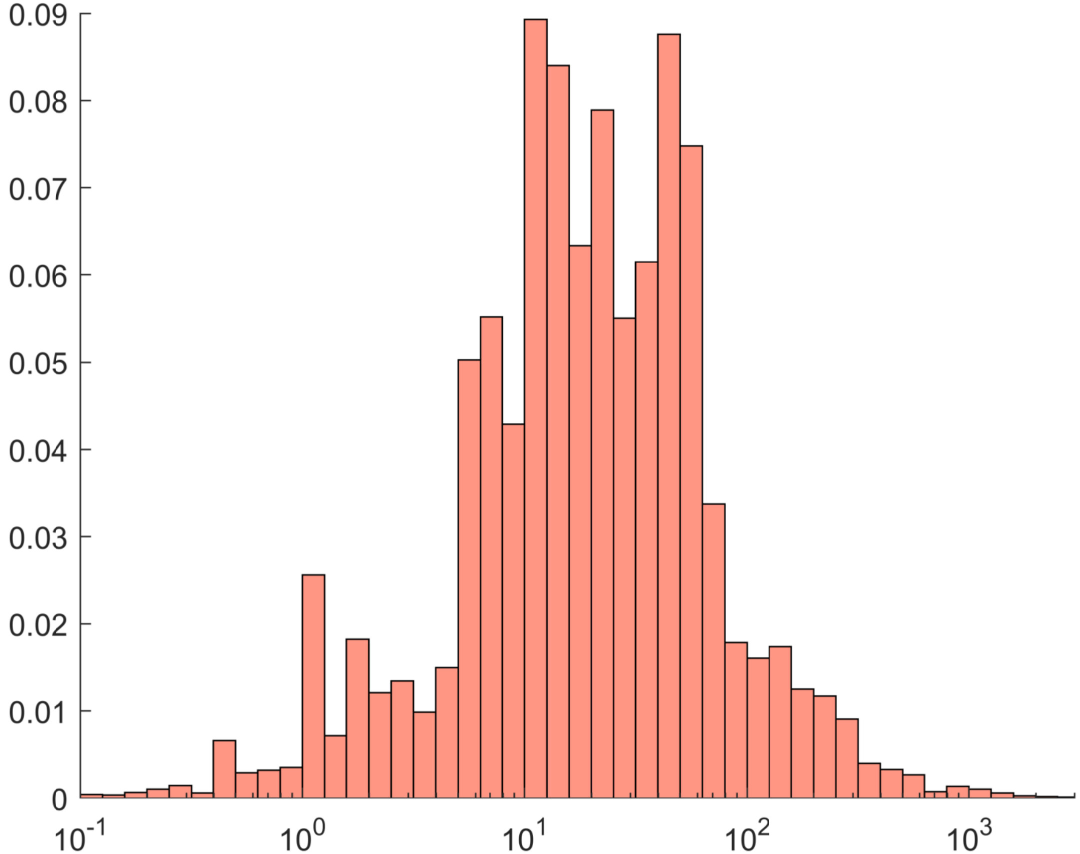


Figure 57: Histogram of carbon intensity (Scope 2, tCO_2e/\$ mn)

Source: Trucost Database (2021) & author's calculations.

Carbon risk measurement

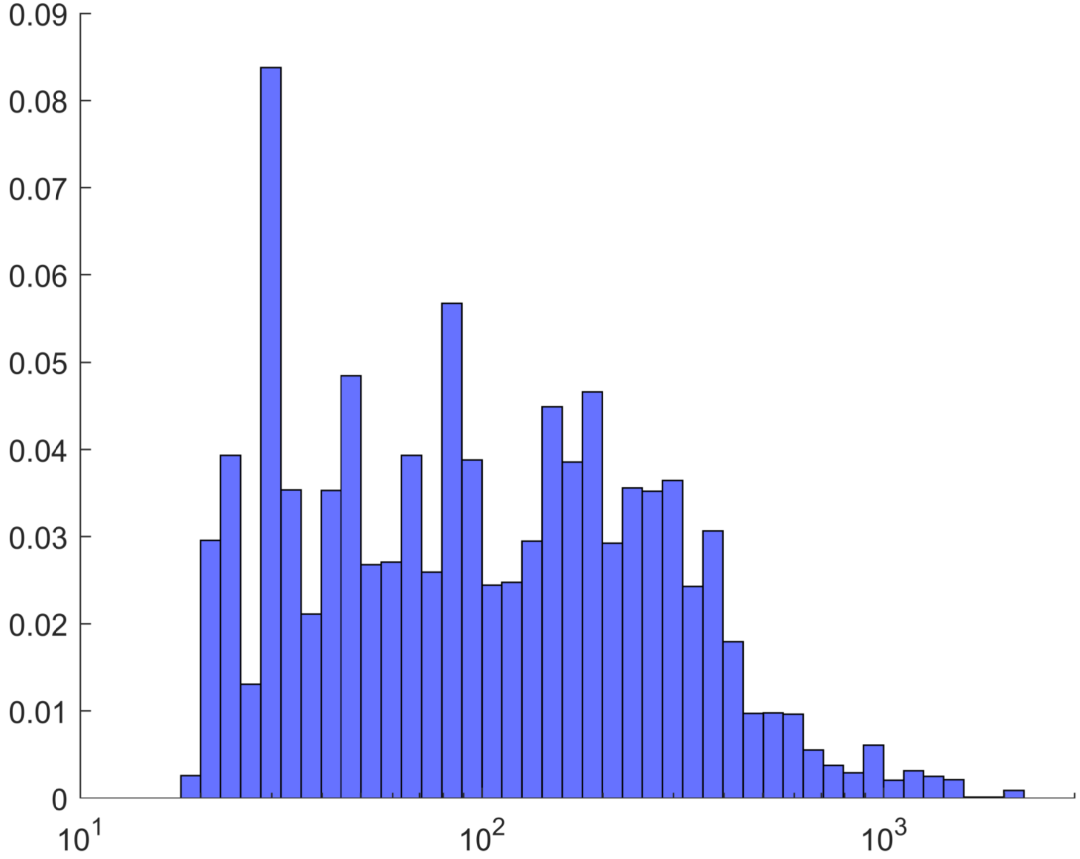


Figure 58: Histogram of carbon intensity (Scope 3, tCO_2e/\$ mn)

Source: Trucost Database (2021) & author's calculations.

Portfolio optimization with a benchmark

The γ-optimization problem is:

$$\begin{aligned} x^{\star} &= \arg\min \frac{1}{2}\sigma^2(x \mid b) - \gamma x^\top \mu(x \mid b) \\ \text{u.c.} & \begin{cases} \mathbf{1}_n^\top x = 1 & \\ \mathbf{0}_n \leq x \leq \mathbf{1}_n & \text{(no short selling)} \\ x \in \Omega & \end{cases} \end{aligned}$$

where $x = (x_1, \ldots, x_n)$ is the portfolio, $b = (b_1, \ldots, b_n)$ is the benchmark, $\sigma(x \mid b) = \sqrt{(x - b)^\top \Sigma (x - b)}$ is the volatility of the tracking error, $\mu(x \mid b) = (x - b)^\top \mu$ is the expected excess return and $x \in \Omega$ corresponds to additional constraints

Remark

We remind that the objective function can be cast into a QP problem:

$$x^{\star} = \arg\min \frac{1}{2} x^\top \Sigma x - x^\top (\gamma\mu + \Sigma b)$$

Quadratic programming problem

Reminder (Lecture 1)

The formulation of a standard QP problem is:

$$\begin{aligned} x^{\star} &= \arg\min \frac{1}{2} x^{\top} Q x - x^{\top} R \\ &\text{u.c.} \left\{ \begin{array}{l} Ax = B \\ Cx \leq D \\ x^{-} \leq x \leq x^{+} \end{array} \right. \end{aligned}$$

Portfolio decarbonization

We note $\mathcal{CI}_i$ the carbon intensity[8] associated to asset i

- The carbon intensity of the benchmark is equal to:

$$\mathcal{CI}(b) = \sum_{i=1}^{n} b_i \cdot \mathcal{CI}_i = b^\top \mathcal{CI}$$

  where $\mathcal{CI} = (\mathcal{CI}_1, \ldots, \mathcal{CI}_n)$ is the vector of carbon intensities
- The carbon intensity of the portfolio is equal to:

$$\mathcal{CI}(x) = x^\top \mathcal{CI}$$

  $\mathcal{CI}(x)$ is also called the weighted average carbon intensity (WACI)
- The objective is to reduce the carbon intensity of the benchmark by a factor $\pi_{\mathcal{CI}}$:

$$\mathcal{CI}(x) \leq \mathcal{CI}^\star = \pi_{\mathcal{CI}} \cdot \mathcal{CI}(b)$$

[8] It corresponds to the carbon intensity of the company i

Portfolio decarbonization

- We deduce that the optimization problem is:

$$
\begin{array}{rcl}
x^{\star} & = & \frac{1}{2}\sigma^{2}\left(x \mid b\right) \\
& \text{u.c.} & \left\{
\begin{array}{l}
\mathbf{1}_n^{\top} x = 1 \\
\mathbf{0}_n \leq x \leq \mathbf{1}_n \\
\mathcal{CI}\left(x\right) \leq \pi_{\mathcal{CI}} \cdot \mathcal{CI}\left(b\right)
\end{array}
\right.
\end{array}
$$

- The underlying idea is to obtain a decarbonized portfolio $x^{\star}$ such that the tracking error with respect to the benchmark b is the lowest
- The benchmark b can be a current portfolio (active management) or an index portfolio (passive management)

Portfolio decarbonization

- Since the constraint on the carbon intensity is equivalent to:

$$\mathcal{CI}^\top x \leq \pi_{\mathcal{CI}} \cdot \left(b^\top \mathcal{CI}\right)$$

We obtain the following QP problem:

$$\begin{aligned} x^\star &= \frac{1}{2} x^\top \Sigma x - x^\top \Sigma b \\ \text{u.c.} & \left\{ \begin{array}{l} \mathbf{1}_n^\top x = 1 \\ \mathcal{CI}^\top x \leq \pi_{\mathcal{CI}} \cdot \left(b^\top \mathcal{CI}\right) \\ \mathbf{0}_n \leq x \leq \mathbf{1}_n \end{array} \right. \end{aligned}$$

Portfolio decarbonization

- We have the following QP correspondences:

$$
\begin{array}{rcl}
Q & = & \Sigma \\
R & = & \Sigma b \\
A & = & \mathbf{1}_n^\top \\
B & = & 1 \\
C & = & \mathcal{CI}^\top \\
D & = & \mathcal{CI}^\star = \pi_{\mathcal{CI}} \cdot \left(b^\top \mathcal{CI}\right) \\
x^- & = & \mathbf{0}_n \\
x^+ & = & \mathbf{1}_n
\end{array}
$$

Portfolio decarbonization

Example 1

We consider a capitalization-weighted equity index, which is composed of 8 stocks. The weights are equal to 23%, 19%, 17%, 13%, 9%, 8%, 6% and 5%. We assume that their volatilities are equal to 22%, 20%, 25%, 18%, 35%, 23%, 13% and 29%. The correlation matrix is given by:

$$\rho = \begin{pmatrix} 100\% & & & & & & & \\ 80\% & 100\% & & & & & & \\ 70\% & 75\% & 100\% & & & & & \\ 60\% & 65\% & 80\% & 100\% & & & & \\ 70\% & 50\% & 70\% & 85\% & 100\% & & & \\ 50\% & 60\% & 70\% & 80\% & 60\% & 100\% & & \\ 70\% & 50\% & 70\% & 75\% & 80\% & 50\% & 100\% & \\ 60\% & 65\% & 70\% & 75\% & 65\% & 70\% & 80\% & 100\% \end{pmatrix}$$

The carbon intensities (expressed in tCO_2e/\$ mn) are respectively equal to: 100.5, 57.2, 250.4, 352.3, 27.1, 54.2, 78.6 and 426.7.

Portfolio decarbonization

Table 18: Optimal decarbonization portfolios (max-threshold approach)

$\pi_{\mathcal{CI}}$	1.00	0.90	0.80	0.70	0.60	0.50
$x_1^\star$	23.00	20.98	18.97	16.95	14.91	11.96
$x_2^\star$	19.00	21.15	23.30	25.46	28.25	33.40
$x_3^\star$	17.00	16.79	16.59	16.38	14.79	9.05
$x_4^\star$	13.00	9.12	5.24	1.36	0.00	0.00
$x_5^\star$	9.00	10.33	11.67	13.00	14.51	16.92
$x_6^\star$	8.00	9.18	10.37	11.55	12.63	13.59
$x_7^\star$	6.00	8.20	10.40	12.59	14.21	15.06
$x_8^\star$	5.00	4.23	3.47	2.70	0.70	0.00
$\sigma(x^\star)$ (in bps)	0.00	19.32	38.64	57.96	84.74	141.97
$\mathcal{CI}(x)$	155.18	139.66	124.14	108.62	93.11	77.59

- The carbon intensity of the index is equal to 155.18 $tCO_2/\$$ mn
- The tracking error of the portfolio is equal to 141.97 bps if we target a 50% reduction of the carbon intensity

Portfolio decarbonization

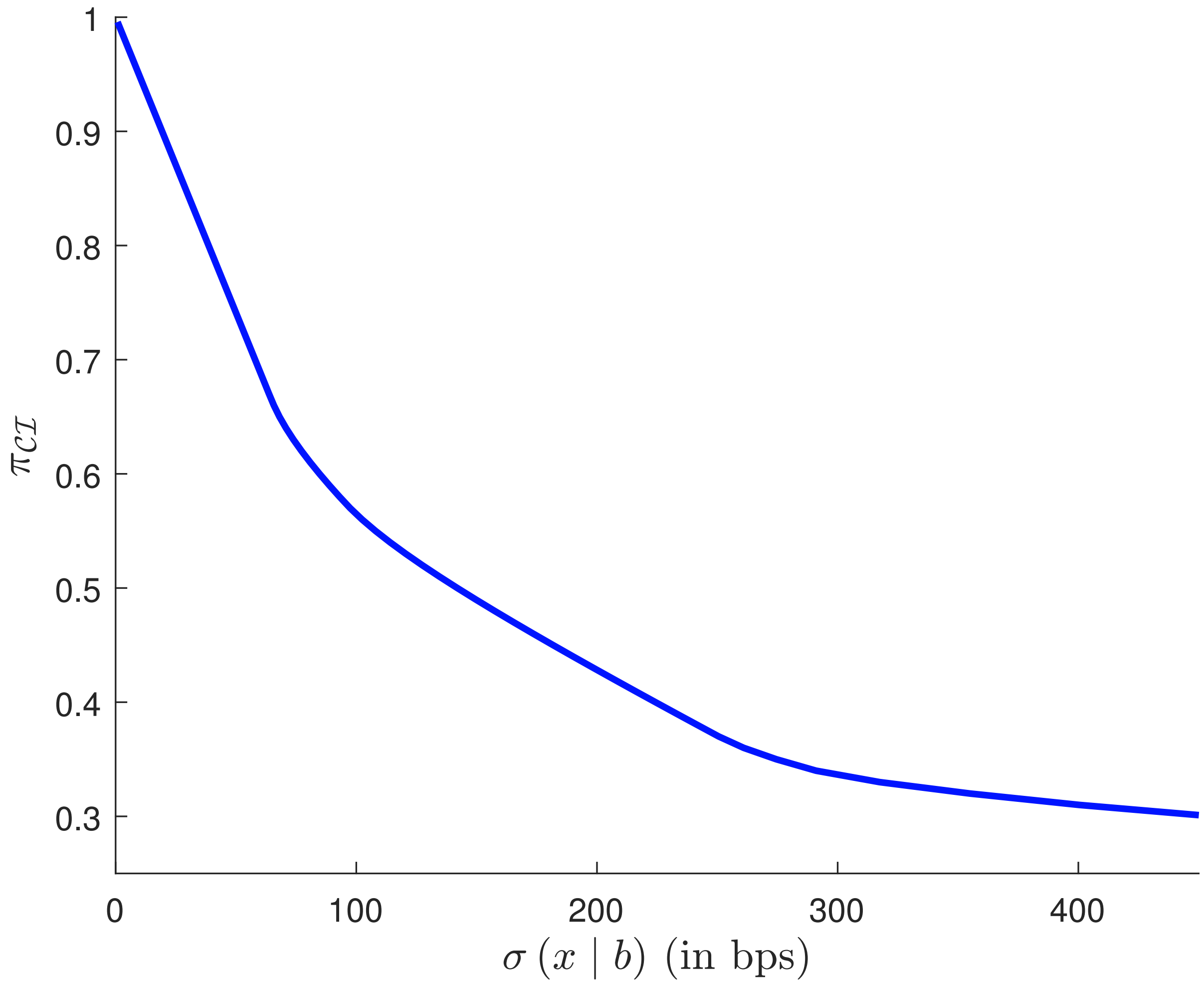


Figure 59: The efficient frontier of optimal decarbonization portfolios

Portfolio decarbonization

Andersson *et al.* (2016) propose a second approach of portfolio decarbonization by eliminating the m worst performer assets in terms of carbon intensity

- We note $\mathcal{CI}_{i:n}$ the order statistics of $\mathcal{CI} = (\mathcal{CI}_1, \ldots, \mathcal{CI}_n)$:

$$\min \mathcal{CI}_i = \mathcal{CI}_{1:n} \leq \mathcal{CI}_{2:n} \leq \cdots \leq \mathcal{CI}_{i:n} \leq \cdots \leq \mathcal{CI}_{n-1:n} \leq \mathcal{CI}_{n:n} = \max \mathcal{CI}_i$$

- The carbon intensity threshold $\mathcal{CI}^{(m,n)}$ is defined as:

$$\mathcal{CI}^{(m,n)} = \mathcal{CI}_{n-m+1:n}$$

  where $\mathcal{CI}_{n-m+1:n}$ is the $(n-m+1)$-th order statistic of $\mathcal{CI}$
- Eliminating the m worst performer assets is equivalent to:

$$\mathcal{CI}_i \geq \mathcal{CI}^{(m,n)} \Rightarrow x_i = 0$$

Portfolio decarbonization

- The optimization problem becomes:

$$
\begin{aligned}
x^{\star} &= \frac{1}{2} x^{\top} \Sigma x - x^{\top} \Sigma b \\
\text{u.c.} & \quad \left\{ \begin{array}{l} \mathbf{1}_n^{\top} x = 1 \\ x_i \in \left\{ \begin{array}{ll} [0, 1] & \text{if } \mathcal{CI}_i < \mathcal{CI}^{(m,n)} \\ \{0\} & \text{if } \mathcal{CI}_i \geq \mathcal{CI}^{(m,n)} \end{array} \right. \end{array} \right.
\end{aligned}
$$

- The last constraint can be written as:

$$\mathbf{0}_n \leq x \leq x^{+}$$

where:

$$x_i^{+} = \mathbb{1}\left\{ \mathcal{CI}_i < \mathcal{CI}^{(m,n)} \right\}$$

We obtain again a QP problem

Portfolio decarbonization

Table 19: Optimal decarbonization portfolios (order-statistic approach)

m	0	1	2	3	4	5	6	7	$\mathcal{CI}$
$x_1^\star$	23.00	18.68	15.94	14.00	**0.00**	0.00	0.00	0.00	100.5
$x_2^\star$	19.00	23.54	26.26	35.84	45.65	56.44	**0.00**	0.00	57.2
$x_3^\star$	17.00	17.46	17.50	**0.00**	0.00	0.00	0.00	0.00	250.4
$x_4^\star$	13.00	6.50	**0.00**	0.00	0.00	0.00	0.00	0.00	352.3
$x_5^\star$	9.00	11.88	13.63	17.98	21.18	26.14	34.73	100.00	27.1
$x_6^\star$	8.00	10.85	12.44	15.84	13.20	17.42	65.27	**0.00**	54.2
$x_7^\star$	6.00	11.11	14.23	16.34	19.98	**0.00**	0.00	0.00	78.6
$x_8^\star$	5.00	**0.00**	0.00	0.00	0.00	0.00	0.00	0.00	426.7
$\sigma(x^\star)$ (in bps)	0.00	77.78	84.51	240.71	278.40	400.71	11.4%	21.6%	
$\mathcal{CI}(x)$	155.18	116.66	96.48	60.87	54.70	48.81	44.79	27.10	

- The reduction of carbon intensity is equal to 24.82% if we eliminate the worst performer
- In this case, we obtain a tracking error of 77.78 bps

Portfolio decarbonization

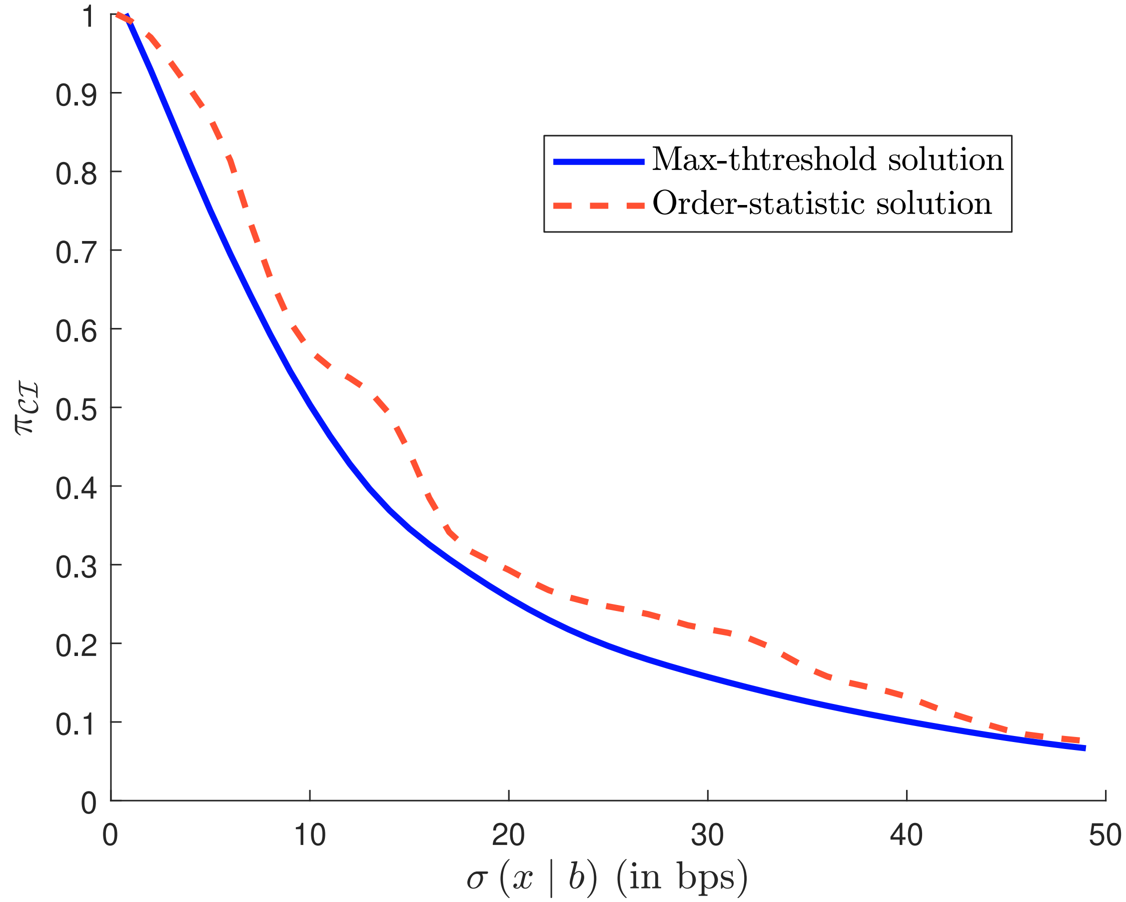


Figure 60: The efficient frontier of optimal decarbonization portfolios (S&P 500 Index, January 2021, Scope 1)

Carbon intensity and the size bias

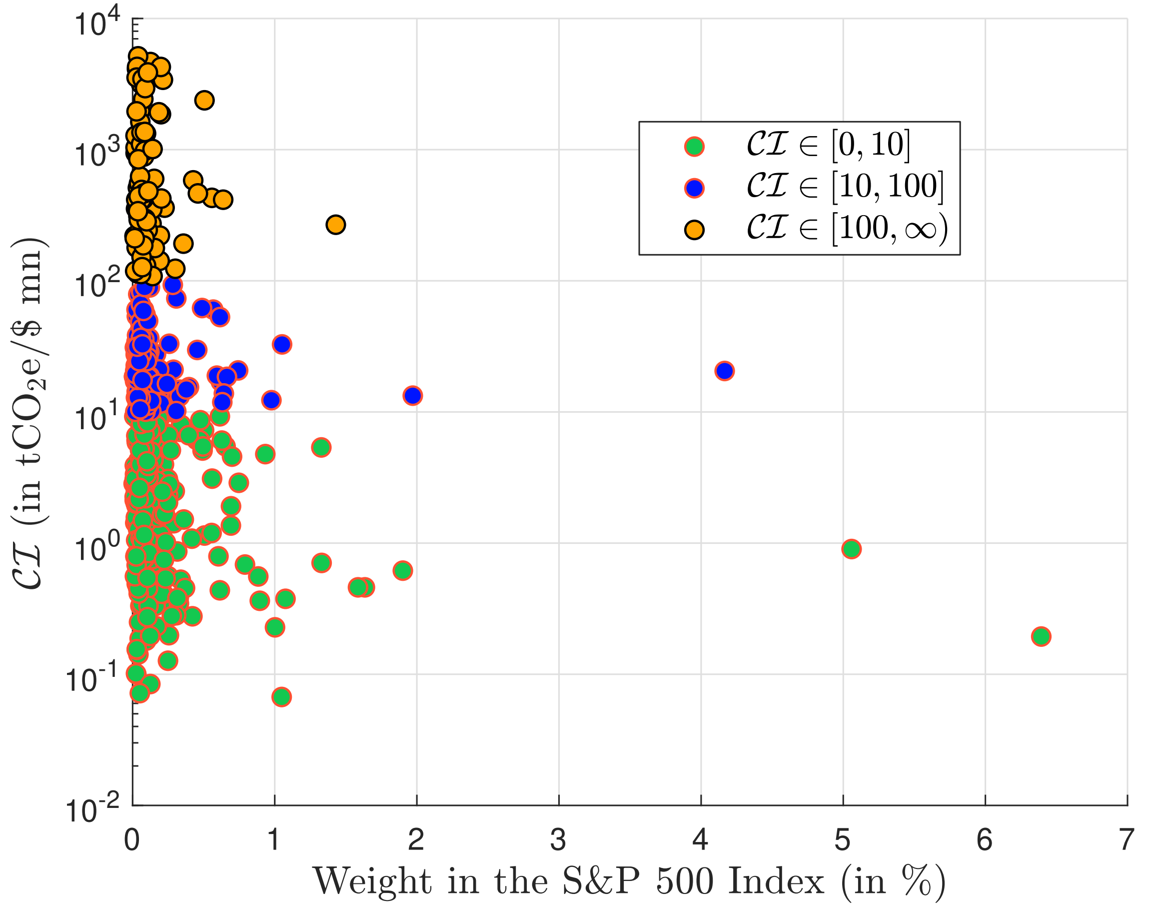


Figure 61: Scatterplot between the index weights b_i and the carbon intensity $\mathcal{CI}_i$ (S&P 500 Index, January 2021, Scope 1)

Carbon intensity and the size bias

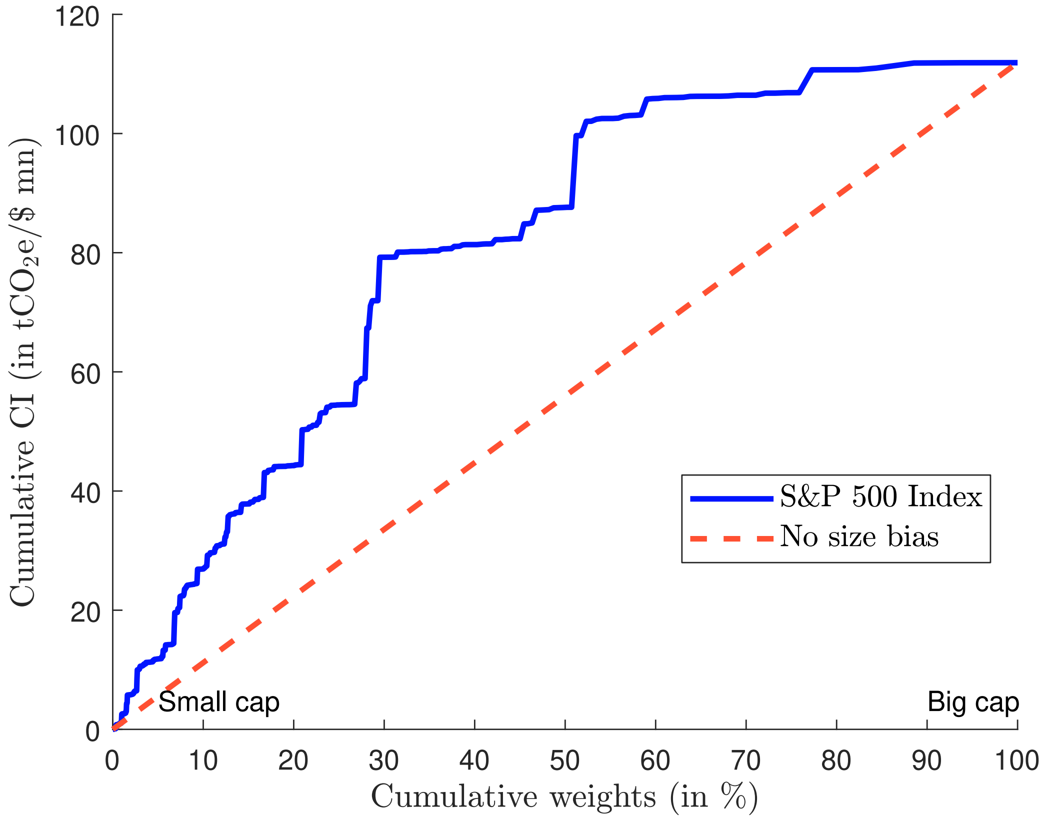


Figure 62: Lorenz curve of the carbon intensity contributions (S&P 500 Index, January 2021, Scope 1)

In January 2021, the Carbon intensity of the S&P 500 Index is equal to 111.89 tCO_2e/\$ mn.

Climate changes indexes

- MSCI Climate Change Indexes — www.msci.com/climate-change-indexes
- MSCI Climate Paris Aligned Indexes — www.msci.com/esg/climate-paris-aligned-indexes
- FTSE Global Climate Index Series — www.ftserussell.com/products/indices/global-climate
- FTSE TPI Climate Transition Index Series — www.ftserussell.com/products/indices/tpi-climate-transition
- FTSE Climate Risk-Adjusted Government Bond Index Series — www.ftserussell.com/products/indices/climate-wgbi
- S&P Climate Indices — www.spglobal.com/spdji/en/index-family/equity/esg/climate
- STOXX Climate Transition Benchmark (CTB) and STOXX Paris-Aligned Benchmark (PAB) Indices — qontigo.com/solutions/climate-indices

Climate changes indexes

- Most of the climate change indices use the following weighting scheme:

$$x_i = \frac{s_i \times b_i}{\sum_{j=1}^{n} s_j \times b_j}$$

  where s_i is the climate change score of the company and b_i is the weight of the company in the parent index (or benchmark)

- The climate change score is generally a combined score based on:
  1. Carbon emission score
  2. Asset stranding score
  3. Climate management score
  4. Green revenue score
  5. Etc.

Financial risk of climate change

The previous approach assumes that the **climate-related market risk** of a company is measured by its **current carbon intensity**

...But the **market perception** of the climate change may be different

Financial risk of climate change

The following analysis is based on the following papers:

- Görgen, M., Jacob, A., Nerlinger, M., Riordan, R., Rohleder, M., and Wilkens, M. (2019), Carbon Risk, *SSRN*, `https://www.ssrn.com/abstract=2930897`.
- Roncalli, T., Le Guenedal, T., Lepetit, F., Roncalli, T., and Sekine, T. (2020), Measuring and Managing Carbon Risk in Investment Portfolios, *Amundi Working Paper*, WP-99-2020, `www.research-center.amundi.com`.

Financial risk of climate change

Goal

The main objective is to define a **market** measure of carbon risk

Three-step approach

- Defining a brown green score (BGS) for each stock (scoring model)
- Building a brown minus green factor (Fama-French approach)
- Estimating the carbon beta of a stock with respect to the BMG factor (Multi-factor regression analysis)

Carbon beta = **market** measure of carbon risk

$\neq$

Carbon intensity = **fundamental** measure of carbon risk

Financial risk of climate change

The example of carbon intensity

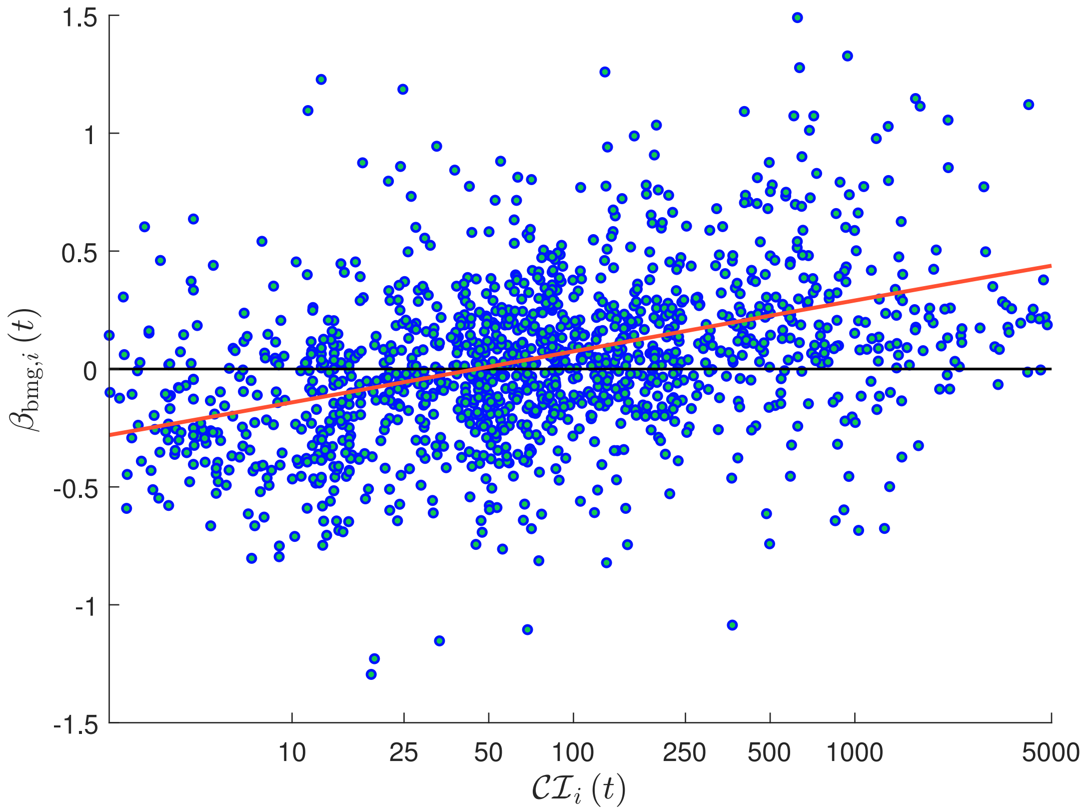


Figure 63: Market-based vs fundamental-based measures of carbon risk

$\Rightarrow$ The market perception of a carbon risk measure depends on several dimensions: sector, country, etc.

Which carbon risk?

Systematic carbon risk

- Common risk
- Carbon beta

Idiosyncratic carbon risk

- Specific risk
- Carbon intensity

Market measure ($\approx$ general carbon risk exposure, e.g. market repricing risk)

Fundamental measure ($\approx$ specific carbon risk exposure, e.g. reputational risk)

Construction of the BMG factor

Risk factor approach (Fama-French)

	Green	Neutral	Brown
Small	SG	SN	SB
Big	BG	BN	BB

The BMG factor return $R_{\mathrm{bmg}}(t)$ is derived from the Fama-French method:

$$R_{\mathrm{bmg}}(t) = \frac{1}{2}\left(R_{\mathrm{SB}}(t) + R_{\mathrm{BB}}(t)\right) - \frac{1}{2}\left(R_{\mathrm{SG}}(t) + R_{\mathrm{BG}}(t)\right)$$

where the returns of each portfolio $R_j(t)$ (small green SG, big green BG, small brown SB, big brown BB) is value-weighted by the market capitalisation

$\Rightarrow$ The BMG factor is a Fama-French risk factor based on a scoring system (brown green score or BGS)

Construction of the BGS

The CARIMA approach

- Carbon Risk Management (CARIMA)
- Project sponsored by the German Federal Ministry of Education and Research
- They publish the carbon risk factor Brown-Minus-Green (BMG)
- They also provide an excel tool
- Contact: Martin Nerlinger (martin.nerlinger@wiwi.uni-augsburg.de)

https://carima-project.de/en/downloads

Construction of the BGS – The CARIMA approach

Görgen *et al.* (2019) use 55 proxy variables to define the brown green score:

- Value chain (impact of a climate policy or a cap-and-trade system on the different activities of a firm) — VC
- Public perception (external environmental image of a firm) — PP
- Adaptability (capacity of the firm to shift towards a low carbon strategy without strong efforts and losses) — PP

A brown green score (BGS) is created for each stock:

$$\begin{aligned}\mathrm{BGS}_i(t) &= \frac{2}{3}\left(0.7 \cdot \mathrm{VC}_i(t) + 0.3 \cdot \mathrm{PP}_i(t)\right) + \\ &\quad \frac{\mathrm{NA}_i(t)}{3}\left(0.7 \cdot \mathrm{VC}_i(t) + 0.3 \cdot \mathrm{PP}_i(t)\right)\end{aligned}$$

where VC_i is the value chain score of stock i, PP_i is the public perception score of stock i and NA_i is the non-adaptability score of stock i

Cumulative performance of the BMG factor

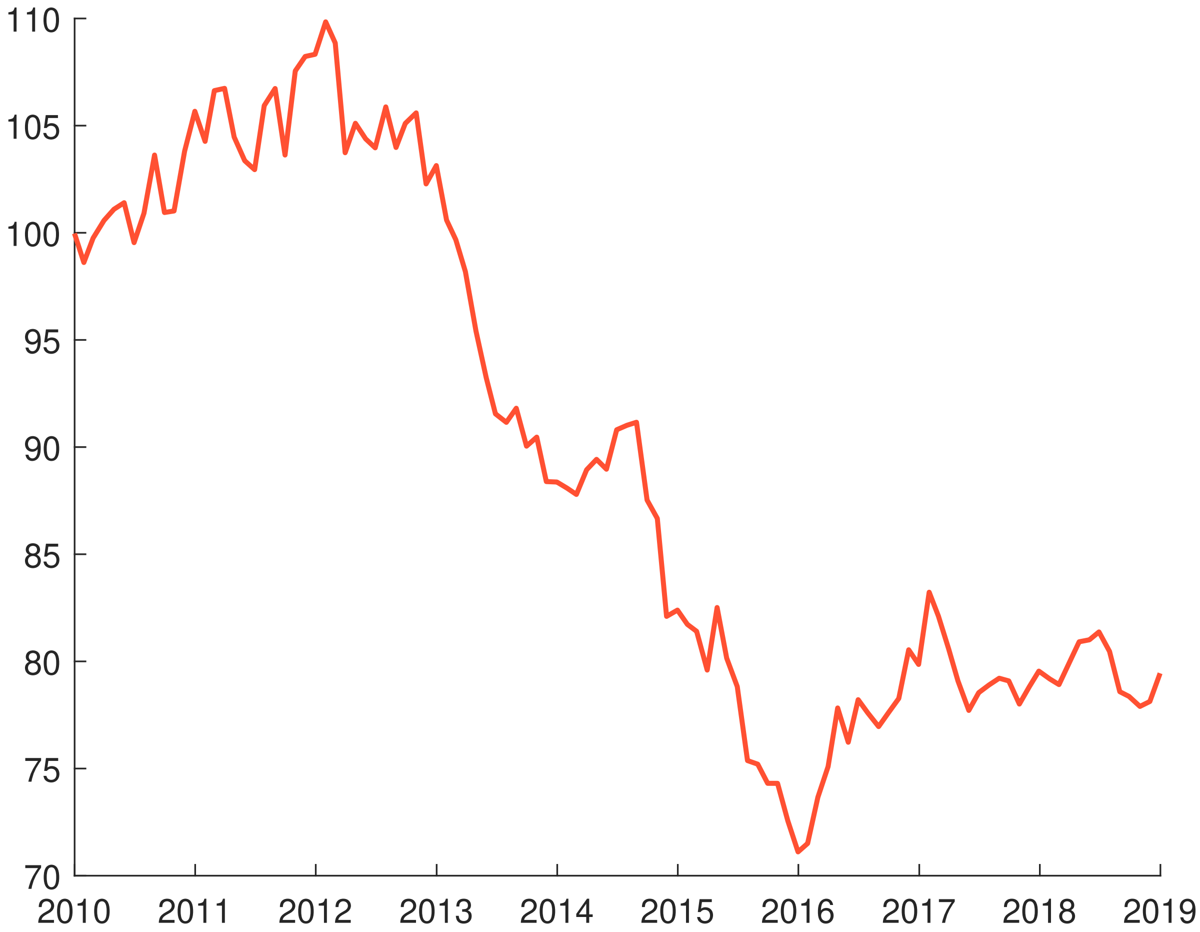


Figure 64: Cumulative performance of the BMG factor

Source: Görgen *et al.* (2019)

Correlation between BMG and other risk factors

Table 20: Correlation matrix of factor returns (in %)

Factor	MKT	SMB	HML	WML	BMG
MKT	100.00***				
SMB	1.41	100.00***			
HML	11.51	−8.93	100.00***		
WML	−14.59	3.87	−41.43***	100.00***	
BMG	5.33	20.33**	27.41***	−21.28**	100.00***

Source: Roncalli *et al.* (2020)

- No significant correlation between market and carbon factors
- Size, value and momentum-specific effects in the BMG factor

Multi-factor analysis

- CAPM

$$R_i(t) = \alpha_i + \beta_{\mathrm{mkt},i} R_{\mathrm{mkt}}(t) + \varepsilon_i(t)$$

- Fama-French 3F model (FF)

$$R_i(t) = \alpha_i + \beta_{\mathrm{mkt},i} R_{\mathrm{mkt}}(t) + \beta_{\mathrm{smb},i} R_{\mathrm{smb}}(t) + \beta_{\mathrm{hml},i} R_{\mathrm{hml}}(t) + \varepsilon_i(t)$$

- MKT+BMG model

$$R_i(t) = \alpha_i + \beta_{\mathrm{mkt},i} R_{\mathrm{mkt}}(t) + \beta_{\mathrm{bmg},i} R_{\mathrm{bmg}}(t) + \varepsilon_i(t)$$

- Extended Fama-French model (FF+BMG)

$$\begin{aligned} R_i(t) &= \alpha_i + \beta_{\mathrm{mkt},i} R_{\mathrm{mkt}}(t) + \beta_{\mathrm{smb},i} R_{\mathrm{smb}}(t) + \beta_{\mathrm{hml},i} R_{\mathrm{hml}}(t) + \\ &\quad \beta_{\mathrm{bmg},i} R_{\mathrm{bmg}}(t) + \varepsilon_i(t) \end{aligned}$$

Multi-factor analysis

- Carhart model (4F)

$$\begin{aligned} R_i(t) &= \alpha_i + \beta_{\mathrm{mkt},i} R_{\mathrm{mkt}}(t) + \beta_{\mathrm{smb},i} R_{\mathrm{smb}}(t) + \beta_{\mathrm{hml},i} R_{\mathrm{hml}}(t) + \\ & \quad \beta_{\mathrm{wml},i} R_{\mathrm{wml}}(t) + \varepsilon_i(t) \end{aligned}$$

- Extended Carhart model (4F+BMG)

$$\begin{aligned} R_i(t) &= \alpha_i + \beta_{\mathrm{mkt},i} R_{\mathrm{mkt}}(t) + \beta_{\mathrm{smb},i} R_{\mathrm{smb}}(t) + \beta_{\mathrm{hml},i} R_{\mathrm{hml}}(t) + \\ & \quad \beta_{\mathrm{wml},i} R_{\mathrm{wml}}(t) + \beta_{\mathrm{bmg},i} R_{\mathrm{bmg}}(t) + \varepsilon_i(t) \end{aligned}$$

$\Rightarrow$ These models are estimated using OLS and stocks that compose the MSCI World Index from January 2010 to December 2018

Relevance of the BMG factor

Table 21: Comparison of cross-section regressions (in %)

	Adjusted $\mathfrak{R}^2$ difference	F-test 10%	5%	1%
CAPM vs FF	1.74	34.6	25.5	13.5
CAPM vs MKT+BMG	1.74	21.2	15.6	9.2
FF vs FF+BMG	1.73	22.5	17.5	9.7
FF vs FF+WML	0.22	6.6	3.0	0.8
4F vs 4F+BMG	1.76	23.6	18.6	10.0

Source: Roncalli *et al.* (2020)

⇒ The effect on the explanatory power is at the same level for the SMB and HML factors together and the BMG factor alone

Sectorial analysis

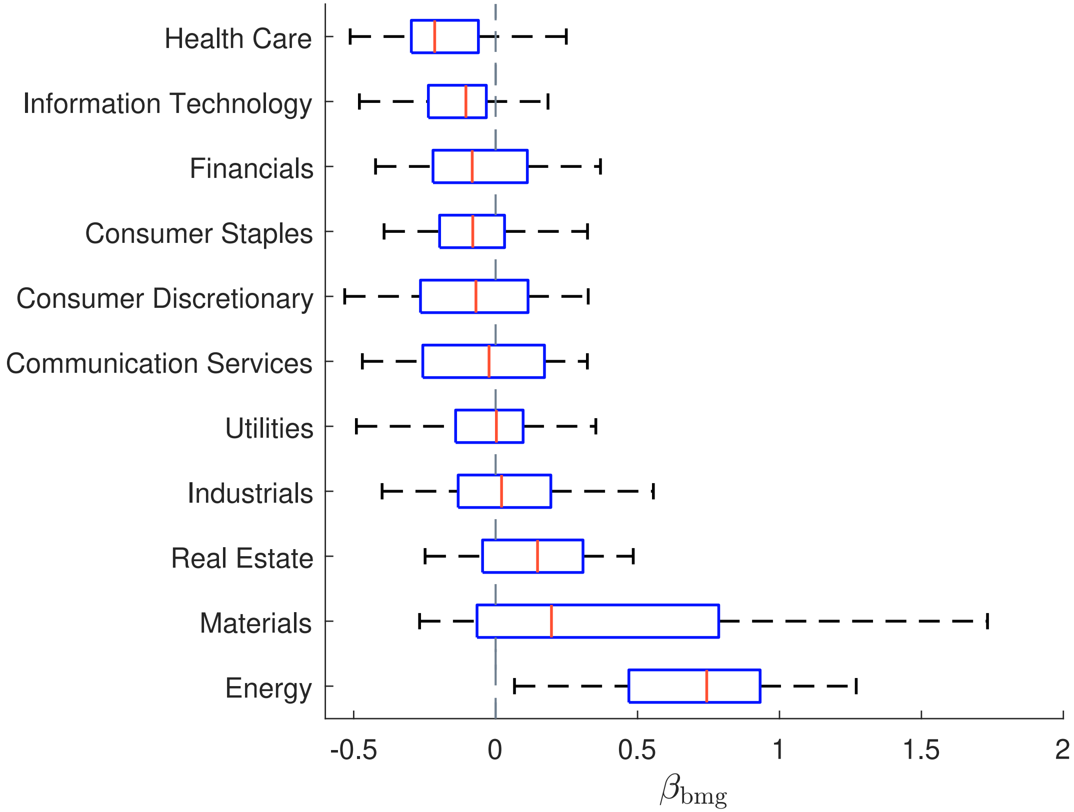


Figure 65: Box plots of the carbon sensitivities[9]

Source: Roncalli *et al.* (2020)

[9] The box plots provide the median, the quartiles and the 5% and 95% quantiles

Absolute versus relative carbon risk

Relative carbon risk

- The right measure is β_{bmg}
- Sign matters
- **Negative exposure** is preferred

Absolute carbon risk

- The right measure is $|\beta_{\mathrm{bmg}}|$
- Sign doesn't matter
- **Zero exposure** is preferred

Two examples

1. We consider three portfolios with a carbon beta of -0.30, -0.05 and $+0.30$ respectively
2. We consider two portfolios with the following characteristics:
   - The value of the carbon beta is $+0.10$ and the stock dispersion of carbon beta is 0.20
   - The value of the carbon beta is -0.30 and the stock dispersion of carbon beta is 1.50

$\Rightarrow$ Impact of portfolio management and theory

Dynamic estimation of β_{bmg}

We use the following dynamic common factor model:

$$R_i(t) = R(t)^\top \beta_i(t) + \varepsilon_i(t)$$

where $R(t) = (1, R_{\mathrm{mkt}}(t), R_{\mathrm{bmg}}(t))$ is the vector of factor returns, $\beta_i(t) = (\alpha_i(t), \beta_{\mathrm{mkt},i}(t), \beta_{\mathrm{bmg},i}(t))$ is the vector of factor betas and $\varepsilon_i(t)$ is a white noise.

Assumption

The state vector $\beta_i(t)$ follows a random walk process:

$$\beta_i(t) = \beta_i(t-1) + \eta_i(t)$$

where $\eta_i(t) \sim \mathcal{N}(\mathbf{0}_3, \Sigma_{\beta,i})$ is the white noise vector and $\Sigma_{\beta,i}$ is the diagonal covariance matrix of the white noise.

$\Rightarrow$ The model is estimated with the Kalman filter

Dynamic estimation of β_{bmg}

State space model (SSM)

- The measurement equation defines the relationship between an observable system y_t and state variables α_t:

$$y_t = Z_t \alpha_t + d_t + \epsilon_t$$

  where y_t is a n-dimensional time series, Z_t is a $n \times m$ matrix, d_t is a $n \times 1$ vector
- The state vector α_t is generated by a Markov linear process:

$$\alpha_t = T_t \alpha_{t-1} + c_t + R_t \eta_t$$

  where α_t is a $m \times 1$ vector, T_t is a $m \times m$ matrix, c_t is a $m \times 1$ vector and R_t is a $m \times p$ matrix
- $\eta_t \sim \mathcal{N}(\mathbf{0}_p, Q_t)$ and $\epsilon_t \sim \mathcal{N}(\mathbf{0}_n, H_t)$ are independent white noise processes of dimension p and n with covariance matrices Q_t and H_t

Dynamic estimation of β_{bmg}

- $\alpha_0 \sim \mathcal{N}(\hat{\alpha}_0, P_0)$ is the initial position of the state vector
- We note $\hat{\alpha}_{t|t}$ (or $\hat{\alpha}_t$) and $\hat{\alpha}_{t|t-1}$ the optimal estimators of α_t given the available information until time t and $t-1$:

$$\begin{aligned} \hat{\alpha}_{t|t} &= \mathbb{E}\left[\alpha_t \mid \mathcal{F}_t\right] \\ \hat{\alpha}_{t|t-1} &= \mathbb{E}\left[\alpha_t \mid \mathcal{F}_{t-1}\right] \end{aligned}$$

- $P_{t|t}$ (or P_t) and $P_{t|t-1}$ are the covariance matrices associated to $\hat{\alpha}_{t|t}$ and $\hat{\alpha}_{t|t-1}$:

$$\begin{aligned} P_{t|t} &= \mathbb{E}\left[\left(\hat{\alpha}_{t|t} - \alpha_t\right)\left(\hat{\alpha}_{t|t} - \alpha_t\right)^\top\right] \\ P_{t|t-1} &= \mathbb{E}\left[\left(\hat{\alpha}_{t|t-1} - \alpha_t\right)\left(\hat{\alpha}_{t|t-1} - \alpha_t\right)^\top\right] \end{aligned}$$

Dynamic estimation of β_{bmg}

Kalman filter

- These different quantities are calculated thanks to the Kalman filter, which consists in the following recursive algorithm:

$$\left\{\begin{array}{l}\hat{\alpha}_{t|t-1} = T_t \hat{\alpha}_{t-1|t-1} + c_t \\ P_{t|t-1} = T_t P_{t-1|t-1} T_t^\top + R_t Q_t R_t^\top \\ \hat{y}_{t|t-1} = Z_t \hat{\alpha}_{t|t-1} + d_t \\ v_t = y_t - \hat{y}_{t|t-1} \\ F_t = Z_t P_{t|t-1} Z_t^\top + H_t \\ \hat{\alpha}_{t|t} = \hat{\alpha}_{t|t-1} + P_{t|t-1} Z_t^\top F_t^{-1} v_t \\ P_{t|t} = \left(I_m - P_{t|t-1} Z_t^\top F_t^{-1} Z_t\right) P_{t|t-1}\end{array}\right.$$

where:

  - $\hat{y}_{t|t-1} = \mathbb{E}\left[y_t \mid \mathcal{F}_{t-1}\right]$ is the best estimator of y_t given the available information until time $t-1$
  - $v_t \sim \mathcal{N}\left(\mathbf{0}_n, F_t\right)$ is the innovation process

Dynamic estimation of β_{bmg}

- The time-varying risk factor model can be written as a state space model:

$$\left\{ \begin{array}{l} y(t) = x(t)^\top \beta(t) + \varepsilon(t) \\ \beta(t) = \beta(t-1) + \eta(t) \end{array} \right.$$

where $\varepsilon(t) \sim \mathcal{N}\left(0, \sigma_\varepsilon^2\right)$, $\eta(t) \sim \mathcal{N}\left(\mathbf{0}_{K+1}, \Sigma_\beta\right)$ and K is the number of risk factors

- In the case of the MKT+BMG model, $y(t)$ corresponds to the asset return $R_i(t)$, $x(t)$ is a 3×1 vector, whose elements are 1, $R_{\mathrm{mkt}}(t)$ and $R_{\mathrm{bmg}}(t)$ and:

$$\beta(t) = \left(\begin{array}{c} \alpha_i(t) \\ \beta_{\mathrm{mkt},i}(t) \\ \beta_{\mathrm{bmg},i}(t) \end{array} \right)$$

Dynamic estimation of β_{bmg}

- $\beta(0) \sim \mathcal{N}(\beta_0, P_0)$ is the initial position of the state vector
- We note $\hat{\beta}(t \mid t-1) = \mathbb{E}[\beta(t) \mid \mathcal{F}(t-1)]$ and $\hat{\beta}(t \mid t) = \mathbb{E}[\beta(t) \mid \mathcal{F}(t)]$ as the optimal estimators of $\beta(t)$ given the available information until time $t-1$ and t
- $P(t \mid t-1)$ and $P(t \mid t)$ are the covariance matrices associated with $\hat{\beta}(t \mid t-1)$ and $\hat{\beta}(t \mid t)$
- The estimate of $y(t)$ is equal to:

$$\hat{y}(t \mid t-1) = x(t)^\top \hat{\beta}(t \mid t-1)$$

- The innovation process $v(t) = y(t) - \hat{y}(t \mid t-1)$ is equal to:

$$\begin{aligned} v(t) &= x(t)^\top \beta(t) + \varepsilon(t) - x(t)^\top \hat{\beta}(t \mid t-1) \\ &= -x(t)^\top \left(\hat{\beta}(t \mid t-1) - \beta(t)\right) + \varepsilon(t) \end{aligned}$$

- The variance $F(t)$ of the innovation process $v(t)$ is then equal to:

$$F(t) = x(t)^\top P(t \mid t-1) x(t) + \sigma_\varepsilon^2$$

Dynamic estimation of β_{bmg}

- The Kalman filter becomes:

$$\left\{\begin{array}{l}
\hat{\beta}(t \mid t-1) = \hat{\beta}(t-1 \mid t-1) \\
P(t \mid t-1) = P(t-1 \mid t-1) + \Sigma_{\beta} \\
v(t) = y(t) - x(t)^{\top} \hat{\beta}(t \mid t-1) \\
F(t) = x(t)^{\top} P(t \mid t-1) x(t) + \sigma_{\varepsilon}^{2} \\
\hat{\beta}(t \mid t) = \hat{\beta}(t \mid t-1) + \left(\dfrac{P(t \mid t-1)}{F(t)}\right) x(t) v(t) \\
P(t \mid t) = \left(I_{K+1} - \left(\dfrac{P(t \mid t-1)}{F(t)}\right) x(t) x(t)^{\top}\right) P(t \mid t-1)
\end{array}\right.$$

Dynamic estimation of β_{bmg}

- In this model, the parameters σ_ε^2 and Σ_β are unknown and can be estimated by the method of maximum likelihood
- Since $v(t) \sim \mathcal{N}(0, F(t))$, the log-likelihood function is equal to:

$$\ell(\theta) = -\frac{T}{2}\ln(2\pi) - \frac{1}{2}\sum_{t=1}^{T}\left(\ln F(t) + \frac{v^2(t)}{F(t)}\right)$$

  where $\theta = \left(\sigma_\varepsilon^2, \Sigma\right)$
- Maximizing the log-likelihood function requires specifying the initial conditions β_0 and P_0, which are not necessarily known. In this case, we use the linear regression $y(t) = x(t)^\top \beta + \varepsilon(t)$, and the OLS estimates $\hat{\beta}_{\mathrm{ols}}$ and $\hat{\sigma}_\varepsilon^2 \left(X^\top X\right)^{-1}$ to initialize β_0 and P_0

Regional analysis of the relative carbon risk

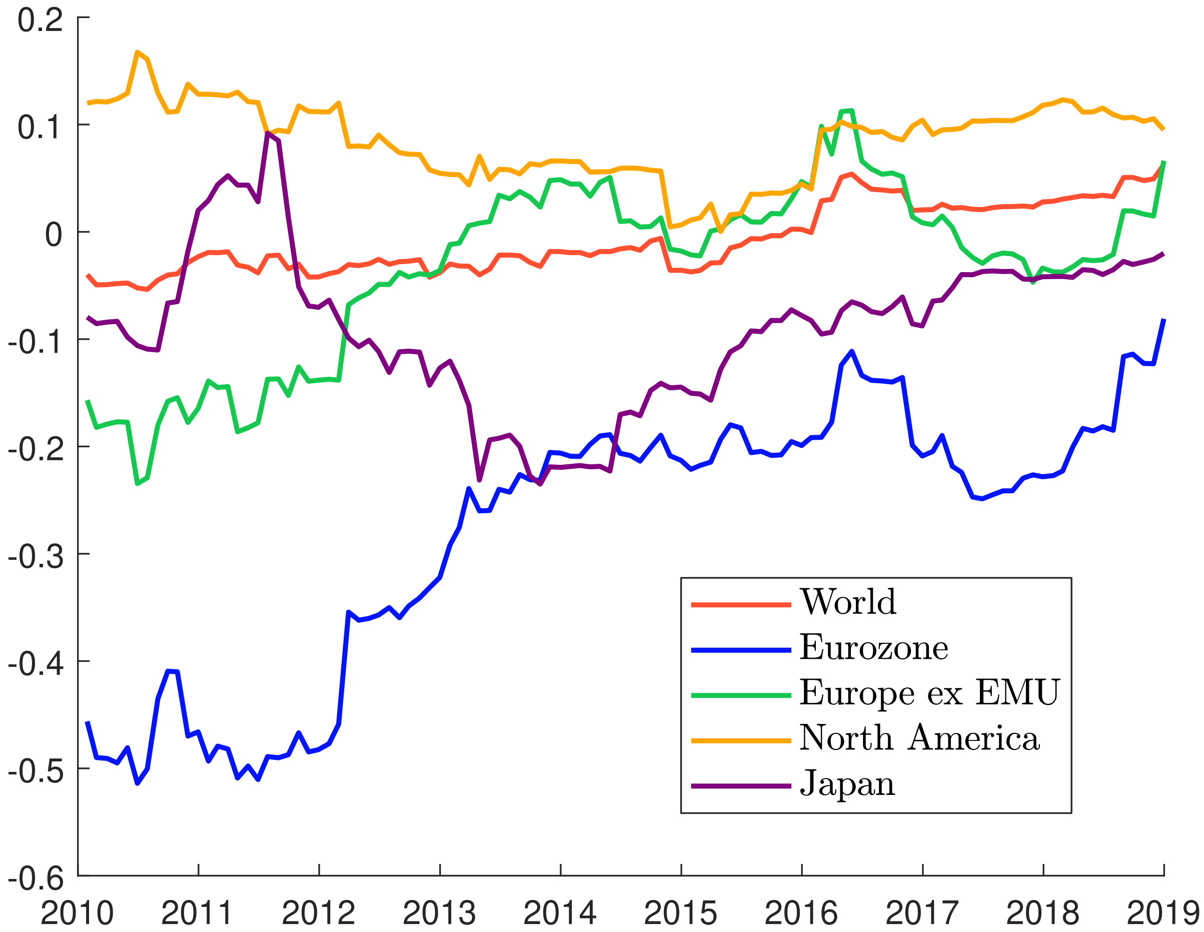


Figure 66: Dynamics of the average relative carbon risk $\beta_{\mathrm{bmg},\mathcal{R}}(t)$ by region

Source: Roncalli *et al.* (2020)

Regional analysis of the absolute carbon risk

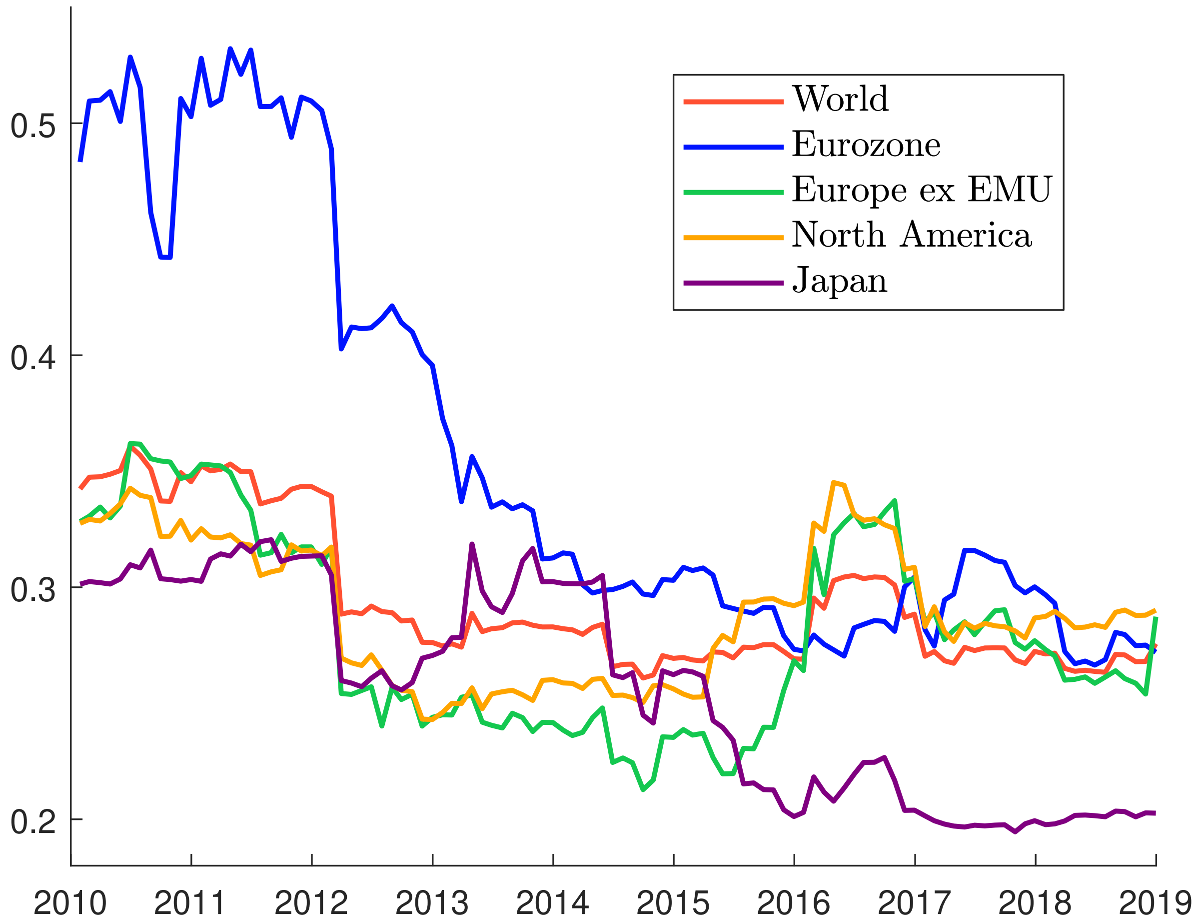


Figure 67: Dynamics of the average absolute carbon risk $|\beta|_{\mathrm{bmg},\mathcal{R}}(t)$ by region

Source: Roncalli *et al.* (2020)

Sectorial analysis

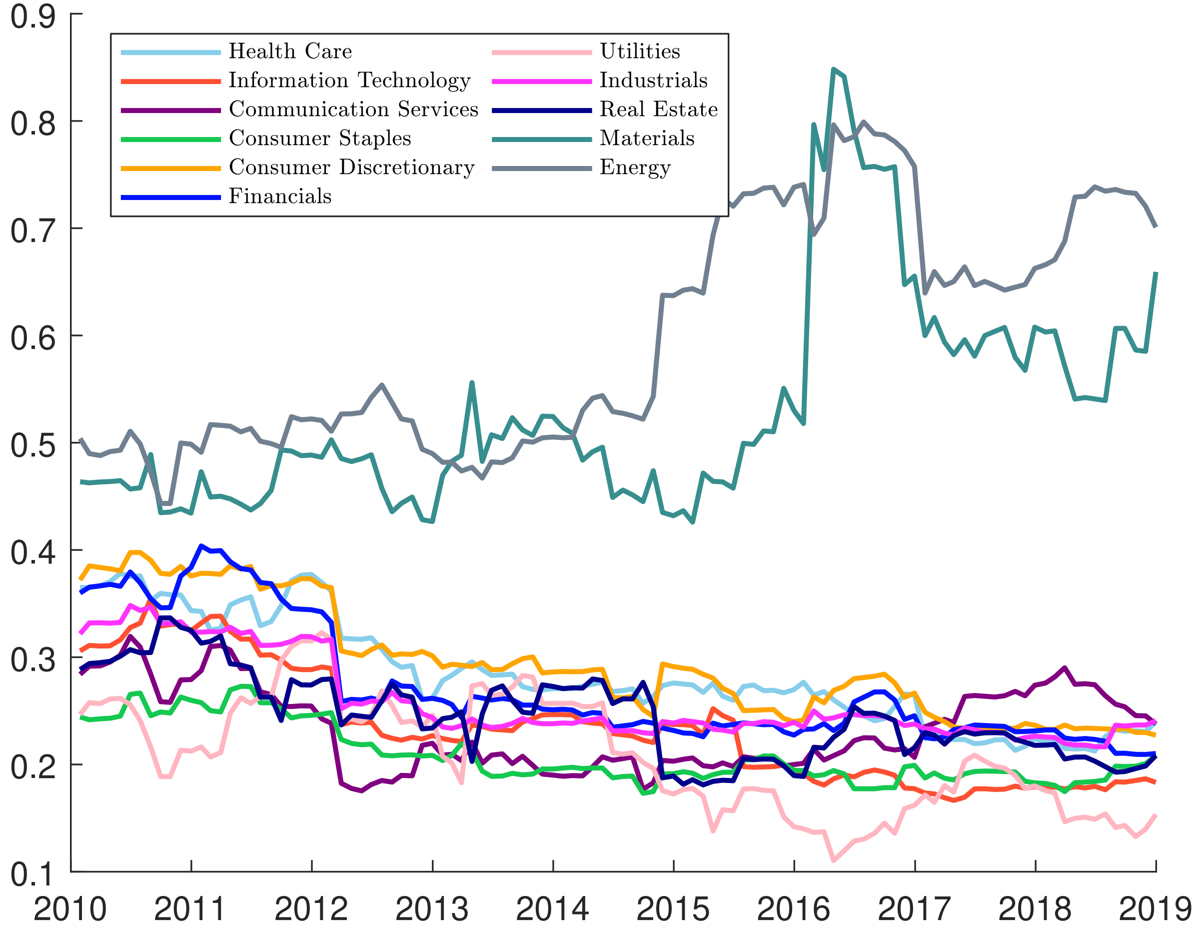


Figure 68: Dynamics of the average absolute carbon risk $|\beta|_{\mathrm{bmg},\mathcal{S}}(t)$ by sector

Source: Roncalli *et al.* (2020)

Advantages and limits of the Carima factor

Advantages

- Biases in the databases are offset because the BGS scores are derived from several databases
- No significant country-specific and sector-specific effects
- No problem of extreme values
- Encompass a lot of climate change-relevant information

Limits

- No differentiation between values near and far the median of a variable
- No rebalancing schemes
- Correlation between BMG factor and some other factors
- Double counting problems
- Not only carbon risk dimension

$\Rightarrow$ Some variables can create more noise than information

Which climate change-related dimensions are the more priced by the market?

Alternative risk factors

We consider the following dimensions

1. Carbon intensity
2. Carbon emissions exposure
3. Carbon emissions management
4. Carbon emissions (exposure + management)
5. Climate change
6. Environmental

Differences with the CARIMA factor

1. Equally-weighted portfolio
2. Integration of the financials sector
3. Rebalancing
4. One variable $\Rightarrow$ no double counting problems

Alternative risk factors

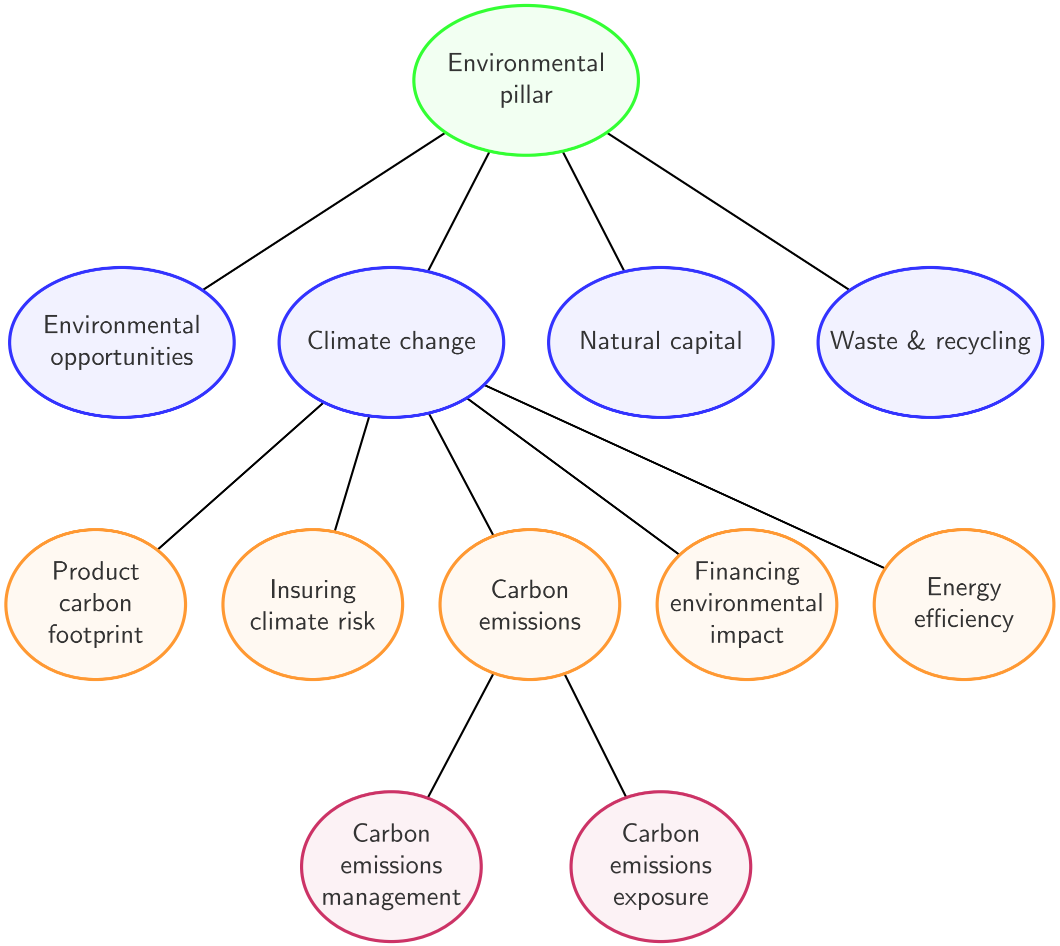


Figure 69: Dimension hierarchy in the environmental pillar (MSCI methodology)

Source: MSCI (2020)

Alternative risk factors

Exposure to carbon costs

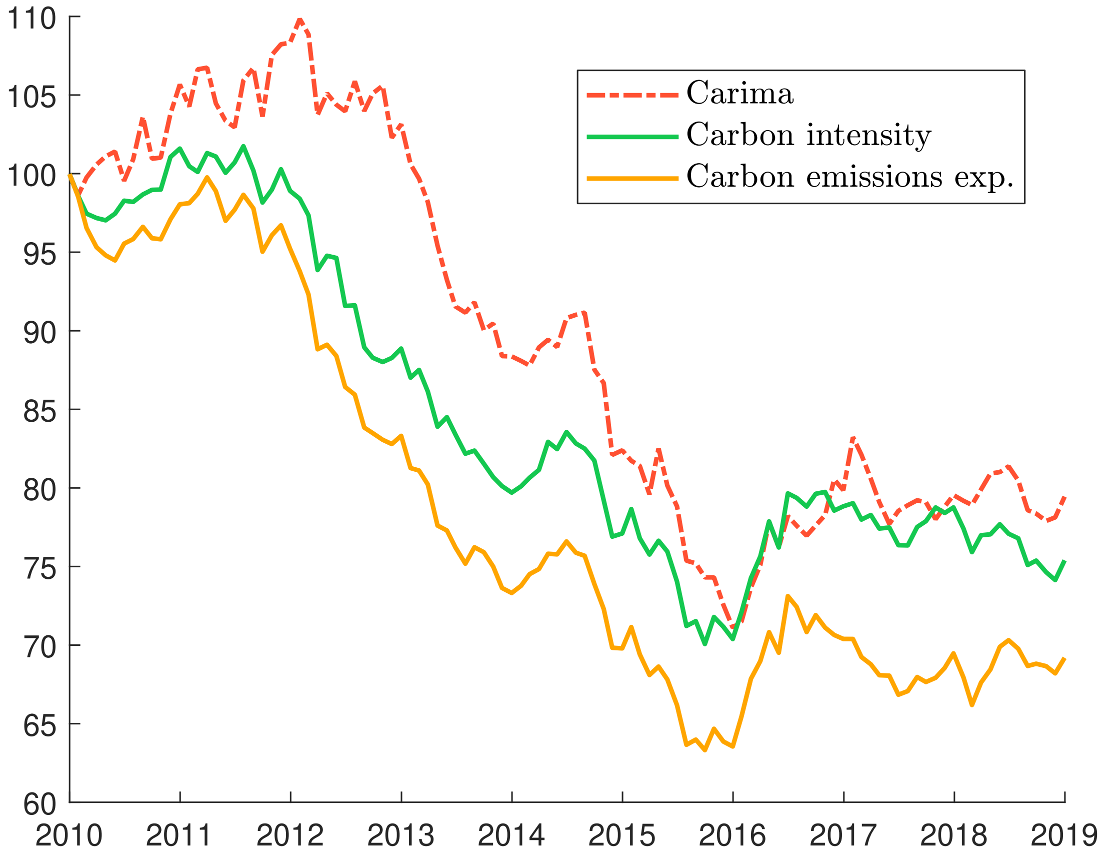


Figure 70: Cumulative performance of the carbon exposure factors

Source: Roncalli *et al.* (2020)

Alternative risk factors

Exposure to carbon costs

Is carbon intensity the unique carbon dimension priced by the market?

Alternative risk factors

Environmental, climate and carbon dimensions

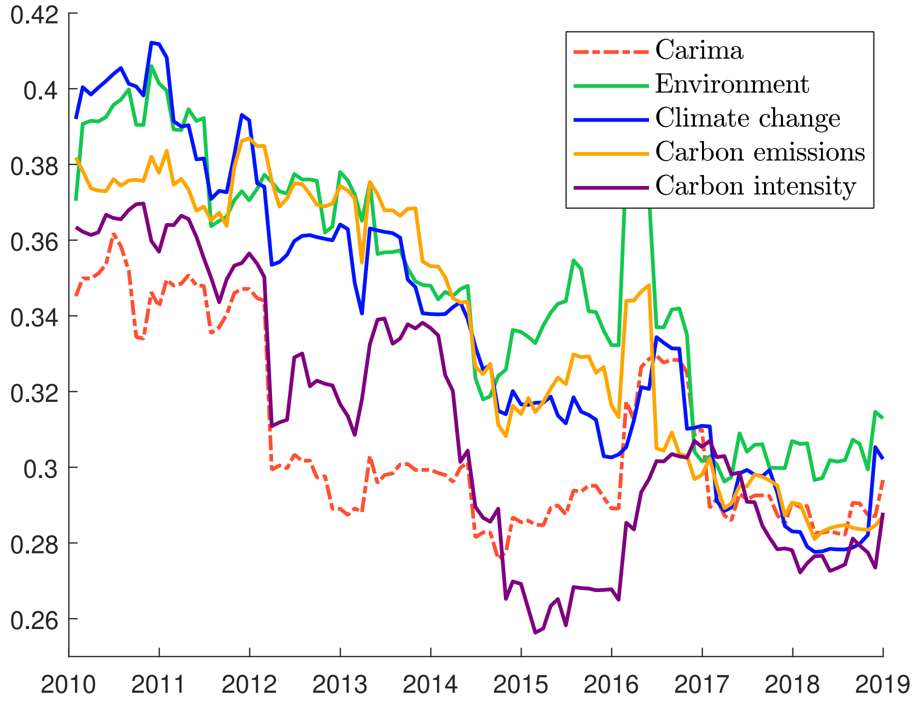


Figure 71: Dynamics of the average absolute carbon risk $|\beta|_{\mathrm{bmg},i}(t)$

Source: Roncalli *et al.* (2020)

Each carbon factor is standardized such that its monthly volatility is equal to the monthly volatility of the market risk

Alternative risk factors

Comparison of the explanatory power

Table 22: Adjusted $\mathfrak{R}^2$ difference

	Full period	1st subperiod	2nd subperiod
Carima	1.74	1.16	2.21
Carbon intensity	1.77	1.43	2.53
Carbon emissions	2.00	2.18	2.39
Climate change	1.58	1.98	1.83
Environment	1.63	1.35	2.17
Carbon intensity*	2.06	1.25	3.13
Carbon emissions*	1.91	1.41	2.42

Source: Roncalli *et al.* (2020)

* *means that the carbon factor is based on the quintile methodology* Q_5 - Q_1

Alternative risk factors

Factor correlations

Table 23: Correlation matrix of factor returns (in %)

Factor	MKT	SMB	HML	WML	BMG
Carbon intensity	−6.46	13.71	8.71	−3.04	58.40***
Carbon emissions exp.	−6.71	14.95	4.03	−4.03	64.02***
Carbon emissions mgmt.	−17.93*	24.16**	−20.91**	20.93**	38.66***
Carbon emissions	1.22	25.85***	−0.23	5.15	72.36***
Climate change	−15.02	16.30*	11.43	2.07	61.11***
Environment	−28.20***	21.16**	−0.33	3.70	68.53***
Carbon intensity*	−18.69*	7.79	−3.64	8.24	54.13***
Carbon emissions*	10.04	27.94***	22.15**	−17.92*	81.42***

Source: Roncalli *et al.* (2020)

Market-specific effect for carbon emissions management, environmental and carbon intensity* factors $\Rightarrow$ bias in a minimum variance portfolio

Portfolio optimization with climate risk

Risk factor model

- We consider the MKT+BMG risk factor model:

$$R_i(t) = \alpha_i + \beta_{\mathrm{mkt},i} R_{\mathrm{mkt}}(t) + \beta_{\mathrm{bmg},i} R_{\mathrm{bmg}}(t) + \varepsilon_i(t)$$

- We assume that $R_{\mathrm{mkt}}(t)$ and $R_{\mathrm{bmg}}(t)$ are uncorrelated
- The covariance matrix is:

$$\Sigma = \beta_{\mathrm{mkt}} \beta_{\mathrm{mkt}}^{\top} \sigma_{\mathrm{mkt}}^2 + \beta_{\mathrm{bmg}} \beta_{\mathrm{bmg}}^{\top} \sigma_{\mathrm{bmg}}^2 + D$$

where β_{mkt} and β_{bmg} are the vector of MKT and BMG betas respectively, σ_{mkt}^2 and σ_{bmg}^2 are the variance of the market and carbon portfolios and $D = \mathrm{diag}\left(\tilde{\sigma}_1^2, \ldots, \tilde{\sigma}_n^2\right)$ is the diagonal matrix of idiosyncratic risks

Application to the minimum variance portfolio

Analytical model

We consider the GMV portfolio:

$$\begin{aligned} x^{\star} &= \arg\min \frac{1}{2} x^{\top} \Sigma x \\ \text{s.t.} & \quad \mathbf{1}_n^{\top} x = 1 \end{aligned}$$

where x is the vector of portfolio weights and Σ is the covariance matrix of stock returns

Application to the minimum variance portfolio

Analytical model

Reminder (Lecture 3)

The solution is equal to:

$$x^{\star} = \frac{\Sigma^{-1}\mathbf{1}_n}{\mathbf{1}_n^{\top}\Sigma^{-1}\mathbf{1}_n}$$

Application to the minimum variance portfolio

Analytical model

Sherman-Morrison-Woodbury (SMW) formula

Suppose u and v are two $n \times 1$ vectors and A is an invertible $n \times n$ matrix. We can show that:

$$\left(A + uv^{\top}\right)^{-1} = A^{-1} - \frac{1}{1 + v^{\top} A^{-1} u} A^{-1} u v^{\top} A^{-1}$$

Application to the minimum variance portfolio

Analytical model

Extended SMW formula

Roncalli *et al.* (2020) show that:

$$\left(A + u_1 v_1^\top + u_2 v_2^\top\right)^{-1} = A^{-1} - A^{-1} U S^{-1} V^\top A^{-1}$$

where $U = \begin{pmatrix} u_1 & u_2 \end{pmatrix}$, $V = \begin{pmatrix} v_1 & v_2 \end{pmatrix}$ and:

$$S = \begin{pmatrix} 1 + v_1^\top A^{-1} u_1 & v_1^\top A^{-1} u_2 \\ v_2^\top A^{-1} u_1 & 1 + v_2^\top A^{-1} u_2 \end{pmatrix}$$

Application to the minimum variance portfolio

Analytical model

In order to compute Σ^{-1}, we apply the extended SMW formula with:

- $A = D$
- $u_1 = v_1 = \sigma_{\mathrm{mkt}} \beta_{\mathrm{mkt}}$
- $u_2 = v_2 = \sigma_{\mathrm{bmg}} \beta_{\mathrm{bmg}}$

It follows that the inverse of the covariance matrix is equal to:

$$\Sigma^{-1} = D^{-1} - D^{-1} U S^{-1} V^\top D^{-1}$$

where:

$$U = V = \begin{pmatrix} \sigma_{\mathrm{mkt}} \beta_{\mathrm{mkt}} & \sigma_{\mathrm{bmg}} \beta_{\mathrm{bmg}} \end{pmatrix}$$

and:

$$S = \begin{pmatrix} 1 + \sigma_{\mathrm{mkt}}^2 \beta_{\mathrm{mkt}}^\top D^{-1} \beta_{\mathrm{mkt}} & \sigma_{\mathrm{mkt}} \sigma_{\mathrm{bmg}} \beta_{\mathrm{mkt}}^\top D^{-1} \beta_{\mathrm{bmg}} \\ \sigma_{\mathrm{mkt}} \sigma_{\mathrm{bmg}} \beta_{\mathrm{mkt}}^\top D^{-1} \beta_{\mathrm{bmg}} & 1 + \sigma_{\mathrm{bmg}}^2 \beta_{\mathrm{bmg}}^\top D^{-1} \beta_{\mathrm{bmg}} \end{pmatrix}$$

Application to the minimum variance portfolio

Analytical model

Reminder (Lecture 3)

In the case of the MKT risk factor model, the solution of the GMV portfolio is equal to:

$$x_i^\star = \frac{\sigma^2\left(x^\star\right)}{\tilde{\sigma}_i^2}\left(1 - \frac{\beta_{\mathrm{mkt},i}}{\beta_{\mathrm{mkt}}^\star}\right)$$

where $\beta_{\mathrm{mkt}}^\star$ is a threshold value

In the case of the MKT+BMG risk factor model, the solution becomes:

$$x_i^\star = \frac{\sigma^2\left(x^\star\right)}{\tilde{\sigma}_i^2}\left(1 - \frac{\beta_{\mathrm{mkt},i}}{\beta_{\mathrm{mkt}}^\star} - \frac{\beta_{\mathrm{bmg},i}}{\beta_{\mathrm{bmg}}^\star}\right)$$

where $\beta_{\mathrm{mkt}}^\star$ and $\beta_{\mathrm{bmg}}^\star$ are two threshold values

Application to the minimum variance portfolio

Analytical model

We consider the long-only MV portfolio:

$$
\begin{aligned}
x^\star & = & \arg\min \frac{1}{2} x^\top \Sigma x \\
& \text{s.t.} & \left\{ \begin{array}{l} \mathbf{1}_n^\top x = 1 \\ \mathbf{0}_n \leq x \leq \mathbf{1}_n \\ x \in \Omega \end{array} \right.
\end{aligned}
$$

where x is the vector of portfolio weights and Σ is the covariance matrix of stock returns

Application to the minimum variance portfolio

Analytical model

In the case of long-only portfolios, we obtain the following formula:

$$x_i^\star = \begin{cases} \dfrac{\sigma^2(x^\star)}{\tilde{\sigma}_i^2}\left(1 - \dfrac{\beta_{\mathrm{mkt},i}}{\beta_{\mathrm{mkt}}^\star} - \dfrac{\beta_{\mathrm{bmg},i}}{\beta_{\mathrm{bmg}}^\star}\right) & \text{if } \dfrac{\beta_{\mathrm{mkt},i}}{\beta_{\mathrm{mkt}}^\star} + \dfrac{\beta_{\mathrm{bmg},i}}{\beta_{\mathrm{bmg}}^\star} \leq 1 \\ 0 & \text{otherwise} \end{cases}$$

where $\beta_{\mathrm{mkt}}^\star$ is a positive threshold and $\beta_{\mathrm{bmg}}^\star$ may be a positive or negative threshold. The MV portfolio selects assets that present a low market beta value but the impact of $\beta_{\mathrm{bmg},i}$ is more complex

Application to the minimum variance portfolio

Analytical model

Low beta, low volatility and negative correlation

$$\rho_{i,j} = \frac{\beta_{\mathrm{mkt},i}\beta_{\mathrm{mkt},j}\sigma^2_{\mathrm{mkt}} + \beta_{\mathrm{bmg},i}\beta_{\mathrm{bmg},j}\sigma^2_{\mathrm{bmg}}}{\sigma_i\sigma_j}$$

where $\beta_{\mathrm{mkt},i}\beta_{\mathrm{mkt},j}$ is generally positive and $\beta_{\mathrm{bmg},i}\beta_{\mathrm{bmg},j}$ is positive or negative. By considering BMG contributions, there is no coherency between low volatility and low correlated assets

Application to the minimum variance portfolio

Applications

Example 2

We consider an investment universe of five assets. Their 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%. We also assume that the market portfolio volatility is equal to 25%

Parameter set #1

We assume that the BMG sensitivities are respectively equal to -0.5, 0.7, 0.2, 0.9 and -0.3, whereas the volatility of the BMG factor is set to 10%

Application to the minimum variance portfolio

Applications

Table 24: Composition of the minimum variance portfolio (parameter set #1)

Asset	$\beta_{\text{mkt},i}$	$\beta_{\text{bmg},i}$	CAPM GMV	CAPM MV	MKT+BMG GMV	MKT+BMG MV
1	0.90	−0.50	147.33	0.00	166.55	33.54
2	0.80	0.70	24.67	9.45	21.37	1.46
3	1.20	0.20	−49.19	0.00	−58.80	0.00
4	0.70	0.90	74.20	90.55	65.06	64.99
5	1.30	−0.30	−97.01	0.00	−94.18	0.00
	$\beta^{\star}_{\text{mkt}}$		1.0972	0.8307	1.0906	0.8667
	$\beta^{\star}_{\text{bmg}}$				19.7724	9.7394

Source: Roncalli *et al.* (2020)

Application to the minimum variance portfolio

Applications

Example 3

We consider an investment universe of five assets. Their 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%. We also assume that the market portfolio volatility is equal to 25%

Parameter set #2

We assume that the BMG sensitivities are respectively equal to -1.5, -0.5, 3.0, -1.2 and -0.9, whereas the volatility of the BMG factor is set to 10%

Parameter set #2

We assume that the BMG sensitivities are respectively equal to 1.5, 0.5, -3.0, 1.2 and 0.9, whereas the volatility of the BMG factor is set to 10%

Application to the minimum variance portfolio

Applications

Table 25: Composition of the minimum variance portfolio (parameter sets #2 and #3)

Asset	$\beta_{\mathrm{mkt},i}$	Parameter set #2			Parameter set #3		
		$\beta_{\mathrm{bmg},i}$	GMV	MV	$\beta_{\mathrm{bmg},i}$	GMV	MV
1	0.90	−1.50	105.46	0.00	1.50	105.46	0.00
2	0.80	−0.50	27.88	19.48	0.50	27.88	19.48
3	1.20	3.00	40.19	13.61	−3.00	40.19	13.61
4	0.70	−1.20	76.77	66.91	1.20	76.77	66.91
5	1.30	−0.90	−150.30	0.00	0.90	−150.30	0.00
$\beta^{\star}_{\mathrm{mkt}}$			1.0982	0.9070		1.0982	0.9070
$\beta^{\star}_{\mathrm{bmg}}$			−19.4470	−9.0718		−19.4470	−9.0718

Source: Roncalli *et al.* (2020)

Application to the minimum variance portfolio

Applications

- MSCI World Index
- December 2018

Remark

The BMG factor is rescaled in order to have the same volatility than the MKT factor $\Rightarrow$ does not change the results, but β and β are now comparable!

Application to the minimum variance portfolio

Absolute carbon risk management

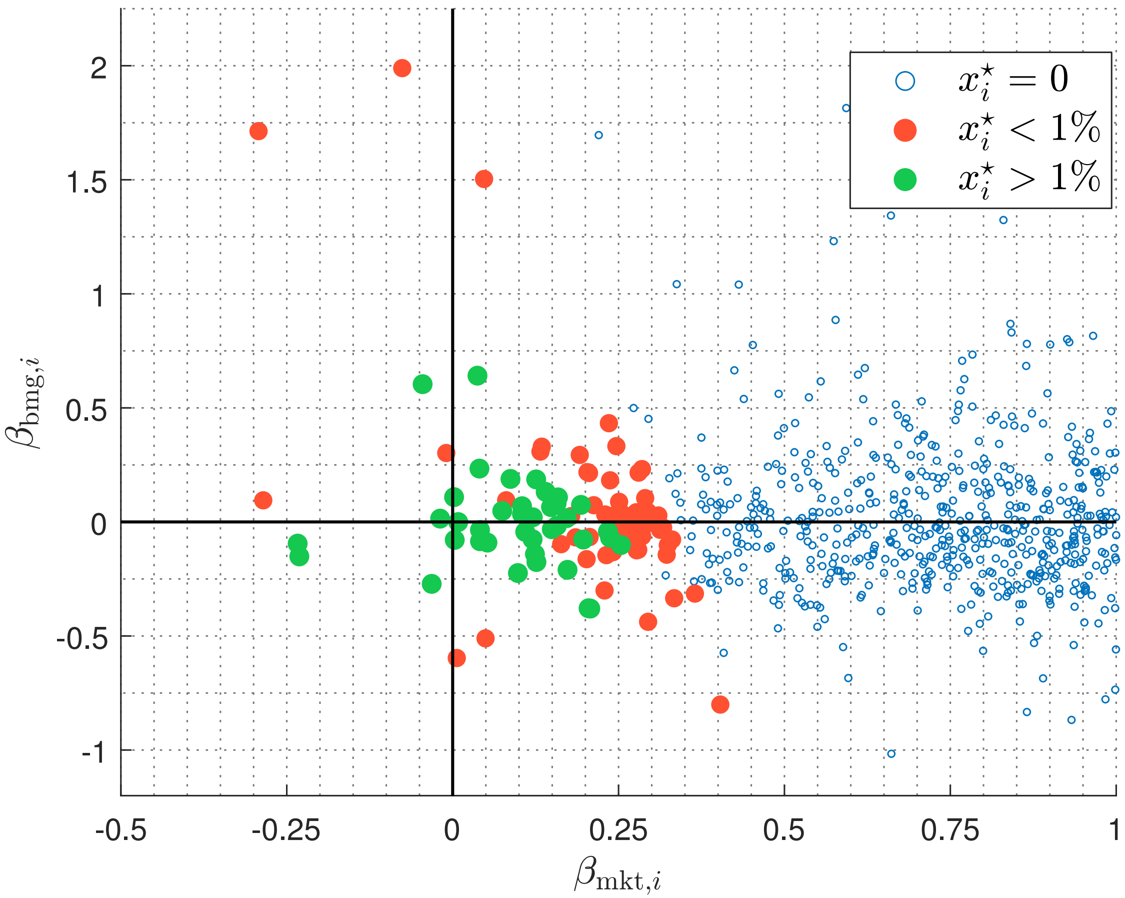


Figure 72: Weights of the MV portfolio (MSCI World Index, Dec. 2018)

Source: Roncalli *et al.* (2021)

Application to the minimum variance portfolio

Absolute carbon risk management

No need to set the constraint:

$$\Omega = \left\{ x \in \mathbb{R}^n : \left| \beta_{\mathrm{bmg}}^\top x \right| \leq \left| \beta \right|_{\mathrm{bmg}}^{+} \right\}$$

where $\left| \beta \right|_{\mathrm{bmg}}^{+}$ is the maximum absolute carbon risk threshold

The minimum variance portfolio reduces naturally the absolute carbon risk without constraint. Indeed, the portfolio's carbon risk is:

$$\beta_{\mathrm{bmg}}^\top x = 0.016$$

The market risk of a stock determine whether it takes into account in the MV portfolio whereas the carbon risk adjusts the weights of the asset

Application to the minimum variance portfolio

Relative carbon risk management

The optimization program becomes:

$$
\begin{aligned}
x^{\star} &= \arg\min \frac{1}{2} x^{\top} \Sigma x \\
\text{s.t.} & \left\{
\begin{array}{l}
\mathbf{1}_n^{\top} x = 1 \\
\beta_{\mathrm{bmg}}^{\top} x \leq \beta_{\mathrm{bmg}}^{+} \\
x \geq \mathbf{0}_n
\end{array}
\right.
\end{aligned}
$$

where β_{bmg}^{+} is the maximum tolerance of the investor with respect to the relative BMG risk

Application to the minimum variance portfolio

Relative carbon risk management

Table 26: Composition of the constrained MV portfolio ($\beta_{\mathrm{bmg}}^{+} = 0$)

Asset	$\beta_{\mathrm{mkt},i}$	Parameter set #1		Parameter set #2		Parameter set #3	
		$\beta_{\mathrm{bmg},i}$	MV	$\beta_{\mathrm{bmg},i}$	MV	$\beta_{\mathrm{bmg},i}$	MV
1	0.90	−0.50	64.29	−1.50	0.00	1.50	0.00
2	0.80	0.70	0.00	−0.50	19.48	0.50	16.11
3	1.20	0.20	0.00	3.00	13.61	−3.00	25.89
4	0.70	0.90	35.71	−1.20	66.91	1.20	58.00
5	1.30	−0.30	0.00	−0.90	0.00	0.90	0.00

Source: Roncalli *et al.* (2020)

Relative carbon risk management

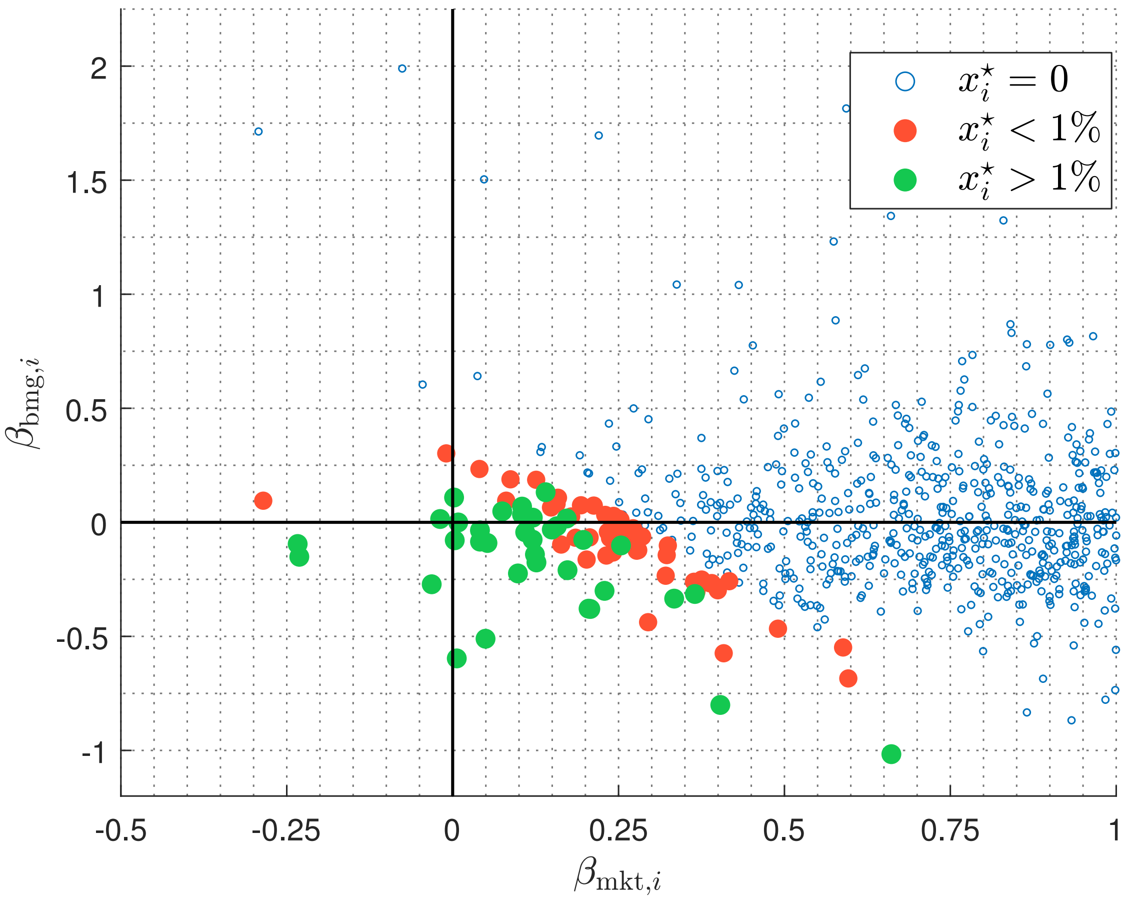


Figure 73: Weights of the constrained MV portfolio ($\beta^+_{\mathrm{bmg}} = -0.25$)

Source: Roncalli *et al.* (2021)

Application to the minimum variance portfolio

Managing both systematic and idiosyncratic carbon risks

- Market-based risk management
  - Absolute carbon risk

$$\left|\sum_{i=1}^{n} x_i \times \beta_{\mathrm{bmg},i}\right| \approx 0$$

  - Relative carbon risk

$$\beta_{\mathrm{bmg}}(x) = \sum_{i=1}^{n} x_i \times \beta_{\mathrm{bmg},i} \leq \beta_{\mathrm{bmg}}^{+}$$

- Fundamental-based risk management
  - Individual threshold

$$x_i = 0 \quad \text{if} \quad \mathcal{CI}_i \leq \mathcal{CI}^{+}$$

    where $\mathcal{CI}_i$ is the carbon intensity of stock i
  - Portfolio threshold

$$\mathcal{CI}(x) = \sum_{i=1}^{n} x_i \times \mathcal{CI}_i \leq \mathcal{CI}^{\star}$$

    where $\mathcal{CI}(x)$ is the weighted average carbon intensity (WACI) of portfolio x

Application to the minimum variance portfolio

Managing both systematic and idiosyncratic carbon risks

- $\beta_{\mathrm{bmg}}(x)$ is the carbon beta of portfolio x
- $\mathcal{CI}(x)$ is the carbon intensity of portfolio x
- $\mathcal{CI}(x)$ is the number of holdings of portfolio x
- β_{bmg}^{+} is the maximum tolerance of the investor with respect to the relative carbon risk of the portfolio
- $\mathcal{CI}^{+}$ is the maximum tolerance of the investor with respect to the carbon intensity of individual assets
- $\mathcal{CI}^{\star}$ is the maximum tolerance of the investor with respect to the carbon intensity of the portfolio
- $\mathrm{WO}(x)$ is the portfolio's weight overlap with respect to the optimized portfolio based only on the CI constraint

Application to the minimum variance portfolio

Managing both systematic and idiosyncratic carbon risks

Table 27: Minimum variance portfolios with a relative carbon beta constraint (MSCI World Index, December 2018)

β_{bmg}^{+}	$\beta_{\mathrm{bmg}}(x)$	$\mathcal{CI}(x)$	$\mathcal{N}(x)$
	1.43%	538	105
-10.00%	-10.00%	501	100
-20.00%	-20.00%	422	89
-40.00%	-40.00%	289	70

Source: Roncalli *et al.* (2021)

Application to the minimum variance portfolio

Managing both systematic and idiosyncratic carbon risks

Table 28: Minimum variance portfolios with a carbon intensity constraint (MSCI World Index, December 2018)

$\mathcal{CI}^{\star}$	$\mathcal{CI}(x)$	$\beta_{\mathrm{bmg}}(x)$	$\mathcal{N}(x)$
500	500	1.43%	105
250	250	1.37%	103
100	100	1.36%	98
50	50	1.33%	82

Source: Roncalli *et al.* (2021)

Application to the minimum variance portfolio

Managing both systematic and idiosyncratic carbon risks

$\Rightarrow$ it makes sense to combine the approaches by imposing two constraints:

$$\begin{cases} \mathcal{CI}(x) \leq \mathcal{CI}^{\star} \\ \beta_{\mathrm{bmg}}(x) \leq \beta_{\mathrm{bmg}}^{+} \end{cases}$$

Table 29: Minimum variance portfolios with carbon beta and intensity constraints — $\beta_{\mathrm{bmg}}^{+} = -20\%$ (MSCI World Index, December 2018)

$\mathcal{CI}^{\star}$	$\mathcal{CI}(x)$	$\beta_{\mathrm{bmg}}(x)$	$\mathcal{N}(x)$	$\mathrm{WO}(x)$
500	430	-20.00%	111	74.65%
250	250	-20.00%	86	75.26%
100	100	-20.00%	79	74.87%
50	50	-20.00%	74	74.99%

Source: Roncalli *et al.* (2021)

Application to enhanced index portfolios

Several optimization approaches

1. Max-threshold optimization solution (integration policy)
2. Order-statistic optimization solution (exclusion policy)
3. Zero-inflated optimization solution (exclusion policy)
4. Neutral-absolute optimization solution (hedging policy)

Application to enhanced index portfolios

Several optimization approaches

The generic optimization problem is:

$$
\begin{aligned}
x^{\star} & = \arg\min \frac{1}{2}(x-b)^{\top}\Sigma(x-b) \\
\text{s.t.} & \quad \left\{
\begin{array}{l}
\mathbf{1}_n^{\top}x = 1 \\
x \geq \mathbf{0}_n \\
x \in \Omega
\end{array}
\right.
\end{aligned}
$$

Application to enhanced index portfolios

Several optimization approaches

1. Max-threshold optimization solution
   - Without a benchmark

$$\Omega = \left\{ x \in \mathbb{R}^n : \beta_{\mathrm{bmg}}^\top x \leq \beta_{\mathrm{bmg}}^+ \right\}$$

   - With a benchmark

$$\Omega = \left\{ x \in \mathbb{R}^n : \beta_{\mathrm{bmg}}^\top (x - b) \leq -\Delta_{\mathrm{bmg}} \right\}$$

Application to enhanced index portfolios

Several optimization approaches

2. Order-statistic optimization solution
   This approach consists in excluding the first m stocks that present the largest carbon beta:

$$\Omega = \left\{ x \in \mathbb{R}^n : x_i = 0 \text{ if } \beta_{\mathrm{bmg},i} \geq \beta_{\mathrm{bmg}}^{(m,n)} \right\}$$

   where $\beta_{\mathrm{bmg}}^{(m,n)} = \beta_{\mathrm{bmg},n-m+1:n}$ is the $(n-m+1)$-*th* order statistic of $(\beta_{\mathrm{bmg},1}, \ldots, \beta_{\mathrm{bmg},n})$

Application to enhanced index portfolios

Several optimization approaches

3. Zero-inflated optimization solution
   This approach exclude the assets with both high weight and high carbon beta:

$$\Omega = \left\{ x \in \mathbb{R}^n : x_i = 0 \text{ if } b_i \beta_{\mathrm{bmg},i} \geq \left(b \odot \beta_{\mathrm{bmg}} \right)^{(m,n)} \right\}$$

   where $\left(b \odot \beta_{\mathrm{bmg}} \right)^{(m,n)} = \left(b \odot \beta_{\mathrm{bmg}} \right)_{n-m+1:n}$ is the $(n-m+1)$-*th* order statistic of the vector $\left(b_1 \beta_{\mathrm{bmg},1}, \ldots, b_n \beta_{\mathrm{bmg},n} \right)$

Application to enhanced index portfolios

Several optimization approaches

4. Neutral-absolute optimization solution
   In this approach, we consider the following constraint:

$$\Omega = \left\{ x \in \mathbb{R}^n : \left| \beta_{\mathrm{bmg}}^\top x \right| \leq |\beta|_{\mathrm{bmg}}^+ \right\}$$

where $|\beta|_{\mathrm{bmg}}^+$ is the maximum sensitivity to absolute carbon risk

Application to enhanced index portfolios

Max-threshold optimization problem

- Δ_{bmg} is the difference between the benchmark's carbon risk and the portfolio's carbon risk
- $\sigma(x \mid b)$ is the tracking error
- $\mathrm{AS}(x \mid b)$ is the active share
- $\mathcal{N}_0(x \mid b)$ is the number of excluding stocks
- $\mathrm{WACI}(x)$ is the weighted average carbon intensity

Application to enhanced index portfolios

Max-threshold optimization problem

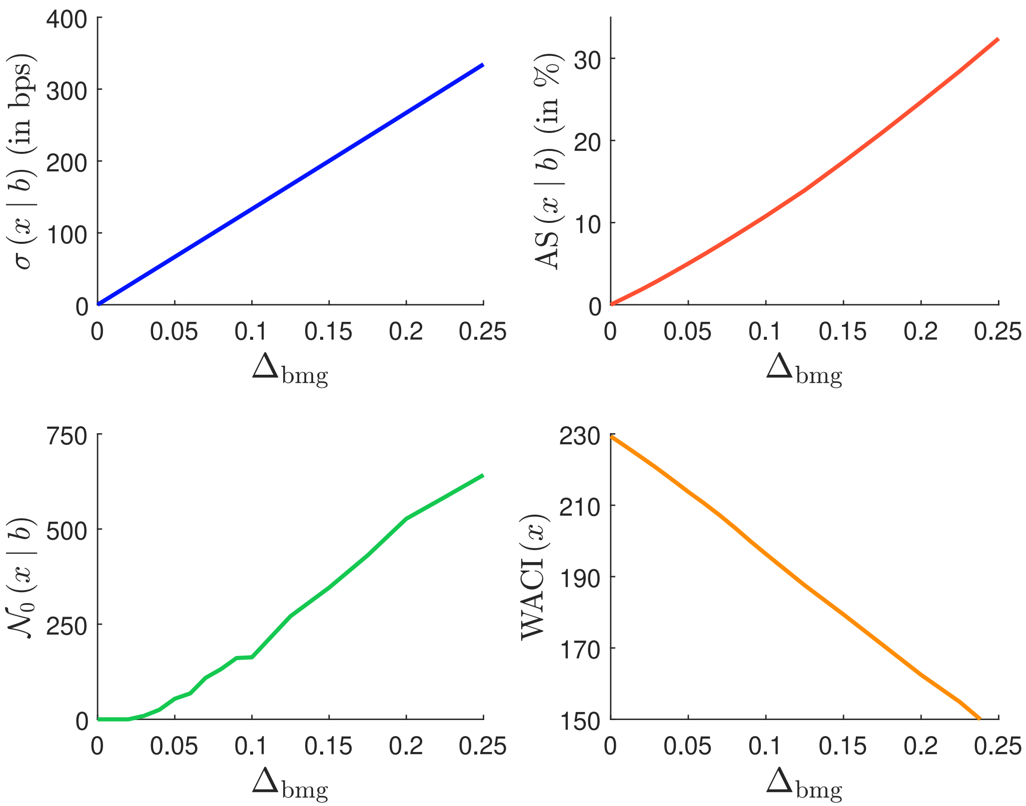


Figure 74: Solution of the max-threshold optimization problem (MSCI World Index, Dec. 2018)

Source: Roncalli *et al.* (2021)

Application to enhanced index portfolios

Order-statistic optimization problem

Remark

The order-statistic (or zero-inflated) optimization problem is less efficient than the max-threshold optimization problem

SRI Investment funds

- Investment vehicles
  - Mutual funds
  - ETFs
  - Mandates & dedicated funds
- Investment strategies
  - Thematic strategies (e.g. water, social, wind energy, climate, plastic, etc.)
  - ESG-tilted strategies (e.g. exclusion, negative screening, best-in-class, enhanced ESG score, controlled TE, etc.)
  - Climate strategies (e.g. low carbon, 2° alignment, activity exclusions[10], etc.)
  - Sustainability-linked securities (e.g. green bonds, social bonds, etc.)

Both α and β management

[10] e.g. coal exploration, oil exploration, electricity generation with a high GHG intensity

SRI Investment funds

Some examples

Mutual funds

- Amundi Climate Transition
- Amundi ARI European Credit SRI
- AXA World Funds – Euro Bonds SRI
- CPR Invest Social Impact
- Fidelity U.S. Sustainability Index
- Fidelity Sustainable Water & Waste
- Natixis ESG Dynamic Fund
- Vanguard FTSE Social Index
- Etc.

ETFs

- Amundi Index MSCI Europe SRI UCITS ETF
- Amundi MSCI Emerging ESG Leaders UCITS ETF
- Amundi EURO ISTOXX Climate Paris Aligned PAB UCITS ETF
- Lyxor New Energy UCITS ETF
- Lyxor World Water UCITS ETF
- SPDR S&P 500 ESG
- First Trust Global Wind Energy ETF
- Invesco S&P 500 ESG UCITS ETF
- Etc.

SRI Investment funds

Regulation

The big issue for an investor is:

How to avoid Greenwashing (& ESG washing)?

Greenwash (also greenwashing)

- Activities by a company or an organization that are intended to make people think that it is concerned about the environment, even if its real business actually harms the environment
- A common form of greenwash is to publicly claim a commitment to the environment while quietly lobbying to avoid regulation

Source: Oxford English Dictionary (2020), `https://www.oed.com`

In finance, greenwashing is understood as making misleading claims about environmental practices, performance or products

SRI Investment funds

Regulation

European sustainable finance labels

- Novethic label (pioneer label in 2009, suspended in 2016)
- French SRI label — https://www.lelabelisr.fr
- FNG label (Germany) — https://fng-siegel.org
- Towards Sustainability label (Belgium) — https://www.towardssustainability.be
- LuxFLAG label (Luxembourg) — https://www.luxflag.org
- Nordic Swan Ecolabel (Nordic countries) — https://www.nordic-ecolabel.org
- Umweltzeichen Ecolabel (Austria) — https://www.umweltzeichen.at/en
- French Greenfin label — https://www.ecologie.gouv.fr/label-greenfin

SRI Investment funds

Regulation

Remark

According to Novethic (2020), 806 funds had a label at the end of December 2019. Nine months later, this number has increased by 392 and the AUM has be multiplied by 3.2!

SRI Investment funds

Regulation

"Today it is difficult for consumers, companies and other market actors to make sense of the many environmental labels and initiatives on the environmental performance of products and companies. There are more than 200 environmental labels active in the EU, and more than 450 active worldwide; there are more than 80 widely used reporting initiatives and methods for carbon emissions only. Some of these methods and initiatives are reliable, some not; they are variable in the issues they cover" (European Commission, 2020).

Source: `https://ec.europa.eu/environment/eussd/index.htm`

SRI Investment funds

Regulation

The High Level Expert Group (HLEG) on Sustainable Finance was created in October 2016 by the European Commission

HLEG 2018 report

- Definition of a taxonomy for sustainable assets
- Inclusion of sustainability and ESG Duties of investors
- Disclosure of ESG metrics
- EU label for green investment funds
- EU standard for green bonds
- Sustainability as part of the mandates of European Supervisory Authorities (ESA)

SRI Investment funds

Regulation

ESMA

- Final report on integrating sustainability risks and factors in the UCITS Directive and the AIFMD (May 2019)
- Final report on integrating sustainability risks and factors in the MIFID II (May 2019)

Green bonds

Definition

Green bonds (or green loans/green debt instruments) are debt instruments where the proceeds will be exclusively applied to finance or re-finance, in part or in full, new and/or existing eligible green projects, and which is aligned with the four core components of the Green Bond Principles (GBP) or the Green Loan Principles.

Source: CBI (2019), `https://www.climatebonds.net`

⇒ Green bonds are "*regular*" bonds[11] aiming at funding projects with positive environmental and/or climate benefits

[11] A regular bond pays regular interest to bondholders

Green bonds

Standardization is strongly required by investors and regulators

- Green Bond Principles[12] (ICMA, 2018)
- Climate Bonds Standard (CBI)
- EU Green Bond Standard[13]
- China's Green Bond Standards[14] (PBOC, 2015)

[12] The first version is published in 2014

[13] The European Green Deal Investment Plan of 14 January 2020 announced that the European Commission will establish a GBS based on the report of the Technical Expert Group on Sustainable Finance (TEG)

[14] See CBI (2020), *China Green Bond Market 2019 Research Report*, `https://www.climatebonds.net/resources/reports/china-green-bond-market-2019-research-report`

Green bonds

Green Bonds Principles

Green Bonds Principles (GBP)

The 4 core components of the GBP are:

1. Use of proceeds
    1. Pollution prevention and control
    2. Biodiversity conservation
    3. Climate change adaptation
2. Process for project evaluation and selection
3. Management of proceeds
4. Reporting

`https://www.icmagroup.org/sustainable-finance/the-principles-guidelines-and-handbooks`

Green bonds

Green Bonds Principles

The use of proceeds includes:

- Renewable energy
- Energy efficiency
- Pollution prevention (e.g. GHG control, soil remediation, waste recycling)
- Sustainable management of living natural resources (e.g. sustainable agriculture, sustainable forestry, restoration of natural landscapes)
- Terrestrial and aquatic biodiversity conservation (e.g. protection of coastal, marine and watershed environments)
- Clean transportation
- Sustainable water management
- Climate change adaptation
- Eco-efficient products
- Green buildings

Green bonds

Green Bonds Principles

With respect to the **process for project evaluation and selection** (component 2), the issuer of a green bond should clearly communicate:

- the environmental sustainability objectives
- the eligible projects
- the related eligibility criteria

The **management of proceeds** (component 3) includes:

- The tracking of the "*balance sheet*" and the allocation of funds[15]
- An external review (not mandatory but highly recommended)

[15] The proceeds should be credited to a sub-account

Green bonds

Green Bonds Principles

The **reporting** (component 4) must be based on the following pillars:

- Transparency
- Description of the projects, allocated amounts and expected impacts
- Qualitative performance indicators
- Quantitative performance measures (e.g. 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)

Types of debt instruments

Asset-linked bond structures

- Regular bond
- Revenue bond
- Project bond
- Green loans

Asset-backed bond structures

- Securitized bond
- Project bond
- ABS/MBS/CLO/CDO
- Covered bond

The green bond market

- Solar bond by the City of San Francisco in 2001
- Equity-linked climate awareness bond by the European Investment Bank (EIB) in 2007
- First green bond issued by the World Bank (in collaboration with Skandinaviska Enskilda Banken) in November 2008

The green bond market

Green bond issuers

- Sovereigns (agencies, municipals, governments)
- Multilateral development banks (MDB)
- Energy and utility companies
- Banks
- Other corporates

Green bond investors

- Pension funds
- Sovereign wealth funds
- Insurance companies
- Asset managers
- Retail investors (e.g. employee savings plans)

Strong imbalance between supply and demand

The green bond market

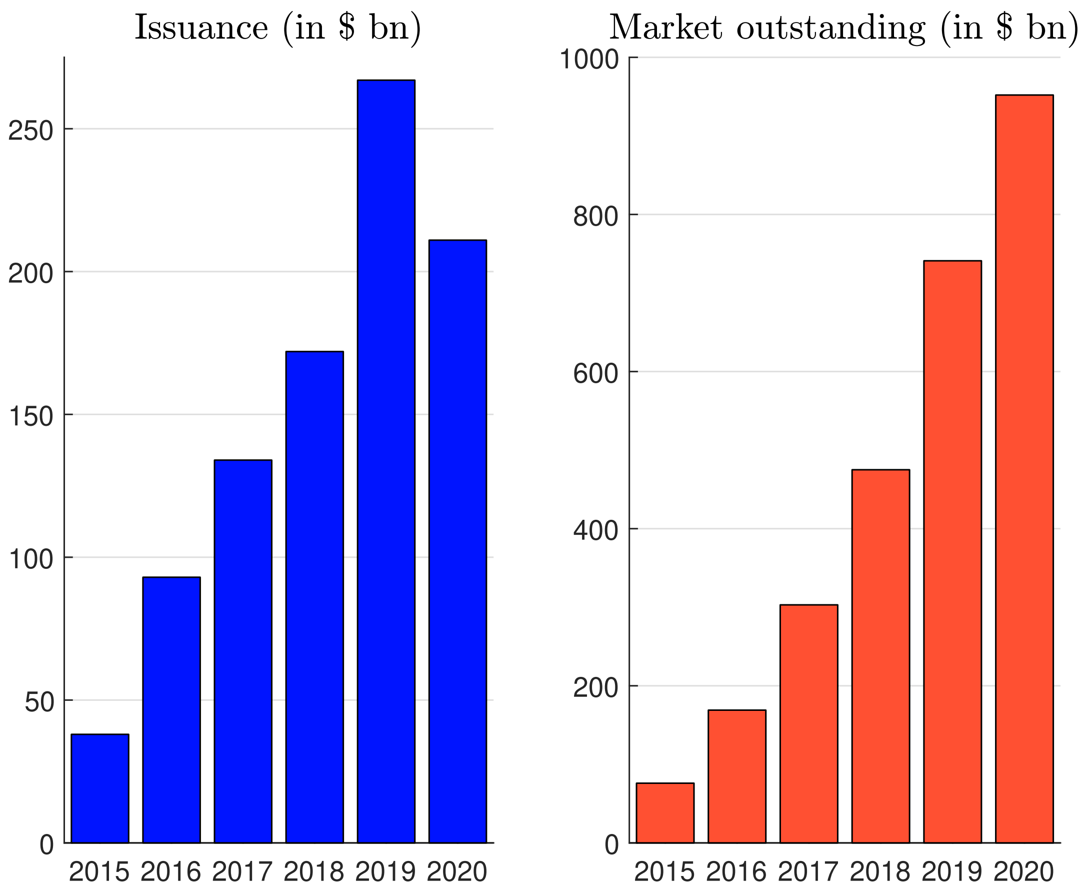
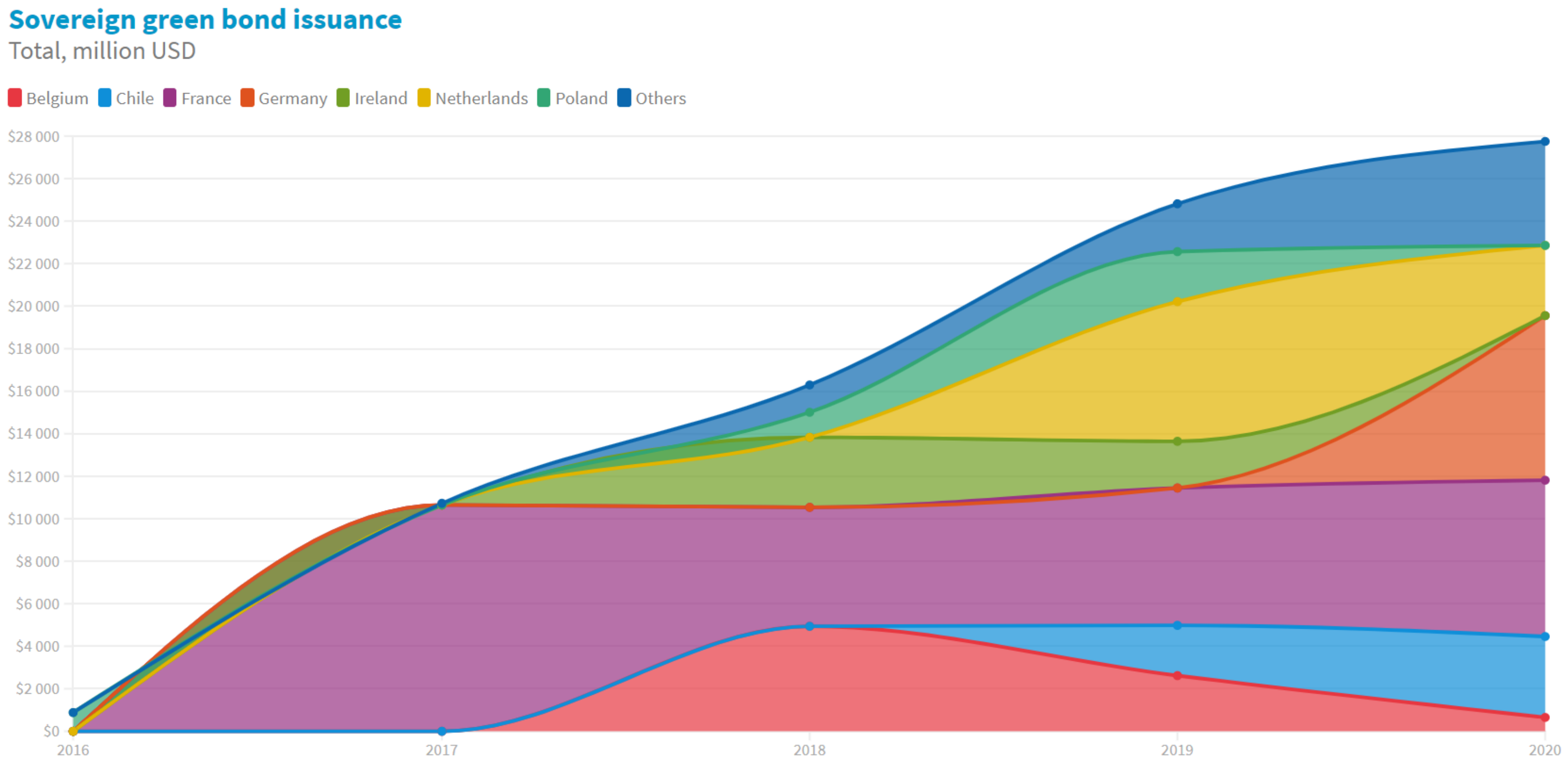


Figure 75: The green bond market

Source: CBI (2020), `https://www.climatebonds.net/market`

The green bond market



Note: Data as at July 2020. "Others" include Fiji (2017), Hong Kong (China) (2019), Hungary (2020), Indonesia (2018, 2019 and 2020), Lithuania (2018), Korea (2019), Nigeria (2017), Seychelles (2018) and Sweden (2020). • Source: OECD (2020), OECD Business and Finance Outlook 2020. © OECD Terms & Conditions

Figure 76: Growing momentum for sovereign green bonds (OECD, Sep. 2020)

Investing in green bonds

Active management

Example of green bond funds:

- Amundi Planet Emerging Green One (EGO), in collaboration with IFC (World Bank)
- Amundi ARI Impact Green Bonds
- AXA WF Global Green Bonds
- BNP Paribas Green Bond
- Mirova Global Green Bond Fund
- Etc.

Investing in green bonds
Passive management

List of green bond indices:

- Bloomberg Barclays MSCI Global Green Bond Index
- S&P Green Bond Index
- Solactive Green Bond Index
- ChinaBond China Climate-Aligned Bond Index:
- ICE BofA Green Index

$\Rightarrow$ ETF and index funds (e.g. Lyxor Green Bond UCITS ETF, iShares Green Bond Index Fund)

The green bond premium

Definition

The green bond premium (or greenium) is the difference in pricing between green bonds and regular bonds

The green bond premium

The greenium debate is a hot topic

You can read the article of the Wall Street Journal written by Matt Wirz[16]:

Why Going Green Saves Bond Borrowers Money

[16] The article is available on the following webpage: https://www.wsj.com/articles/why-going-green-saves-bond-borrowers-money-11608201002

The green bond premium

Table 30: Overview of GB pricing

Study	Market	#GBs	Universe	Period	Method	Greenium
Bachelet *et al.*(2019)	Secondary	89	Global	2013 - 2017	OLS model	2.1/5.9
Bour (2019)	Secondary	95	Global	2014 - 2018	Fixed effects model	−23.2
Ehlers and Packer (2017)	Primary	21	EUR & USD	2014 - 2017	Yield comparison	−18
Fatica *et al.* (2019)	Primary	1 397	Global	2007 - 2018	OLS model	
Hachenberg and Sciereck (2018)	Secondary	63	Global	August 2016	Panel data regression	NS
Hyun *et al* (2020)	Secondary	60	Global	2010 - 2017	Fixed effects GLS model	NS
Karpf and Mandel (2018)	Secondary	1 880	US Municipals	2010 - 2016	Oaxaca-Blinder decomposition	+7.8
Larcker and Watts (2019)	Secondary	640	US Municipals	2013 - 2018	Matching & Yield comparison	NS
Lau *et al.* (2020)	Secondary	267	Global	2013 - 2017	Two-way Fixed effects model	−1.2
Nanayakkara and Colombage (2019)	Secondary	43	Global	2016 - 2017	Panel data with hybrid model	−62.7
Ostlund (2015)	Secondary	28	Global	2011 - 2015	Yield comparison	NS
Preclaw and Bakshi (2015)	Secondary	Index	Global	2014 - 2015	OLS model	−16.7
Schmitt (2017)	Secondary	160	Global	2015 - 2017	Fixed effects model	−3.2
Zerbib (2019)	Secondary	110	Global	2013 - 2017	Fixed effects model	−1.8
Baker *et al.* (2018)	Secondary	2 083 19	US Municipals US Corporates	2010 - 2016 2014 - 2016	OLS model	−7.6/−5.5
Gianfrate and Peri (2019)	Primary Secondary	121 70/118	EUR	2013 - 2017 3 dates in 2017	Propensity score matching	−18 −11/−5
Kapraun and Scheins (2019)	Primary Secondary	1 513 769	Global	2009 - 2018	Fixed effects model	−18 +10
Partridge and Medda (2018)	Primary Secondary	521	US Municipals	2013 - 2018	Yield curve analysis	−4 NS

Source: Ben Slimane *et al.* (2020)

The green bond premium

- From the issuer's point of view, a green bond issuance is more expensive than a conventional issuance due to the need for external review, regular reporting and impact assessments
- From the investor's point of view, there is no fundamental difference between a green bond and a conventional bond, meaning that one should consider a negative green bond premium as a market anomaly

The green bond premium

Ben Slimane *et al.* (2020) test two approaches:

1. Top-down approach
   - Compare a green bond index portfolio to a conventional bond index portfolio
   - Same characteristics in terms of currency, sector, credit quality and maturity
2. Bottom-up approach
   - Compares the green bond of an issuer with a synthetic conventional bond of the same issuer
   - Same characteristics in terms of currency, seniority and duration.

The green bond premium

Main result (Ben Slimane *et al.*, 2020)

The greenium is negative between -5 and -2 bps on average

Other results:

- Differences between sectors, currencies, maturities, regions and ratings
- Transatlantic divided between US and Europe
- The volatility of green bond portfolios are lower than the volatility of conventional bond portfolios $\Rightarrow$ identical Sharpe ratio since the last four years
- Time-varying property of the greenium

The green bond premium

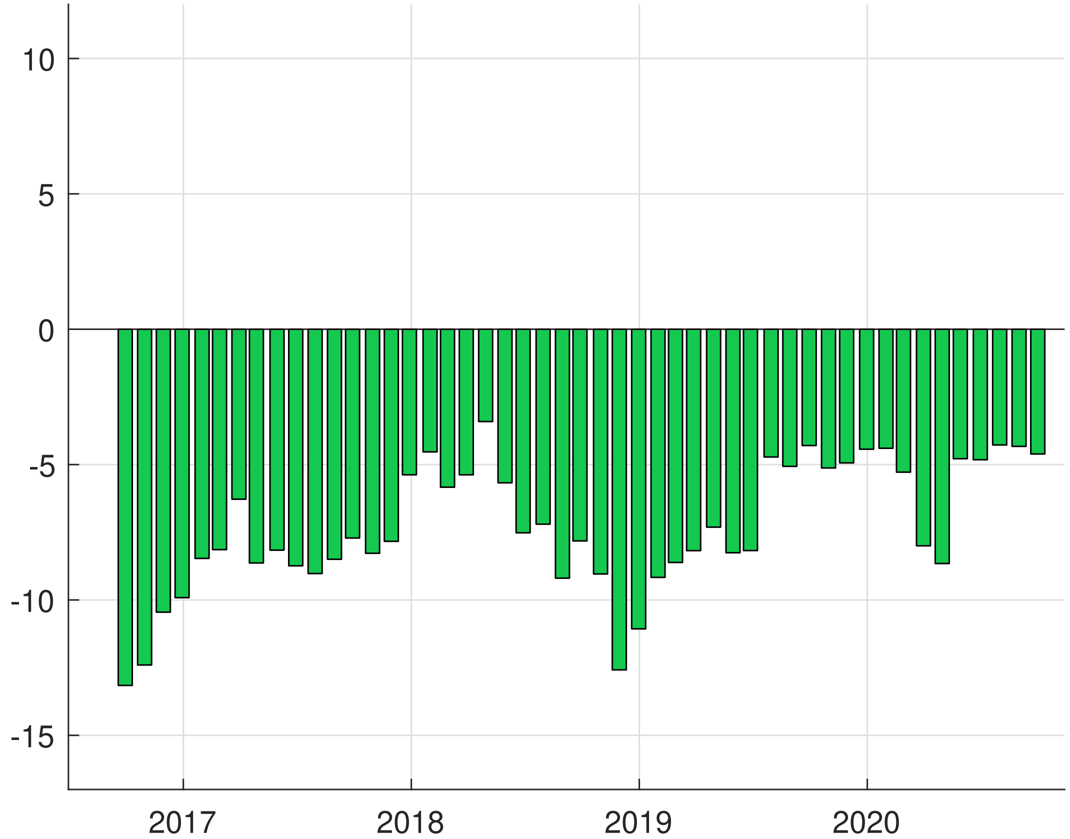


Figure 77: Evolution of the EUR greenium

Source: Ben Slimane *et al.* (2020)

The green bond premium

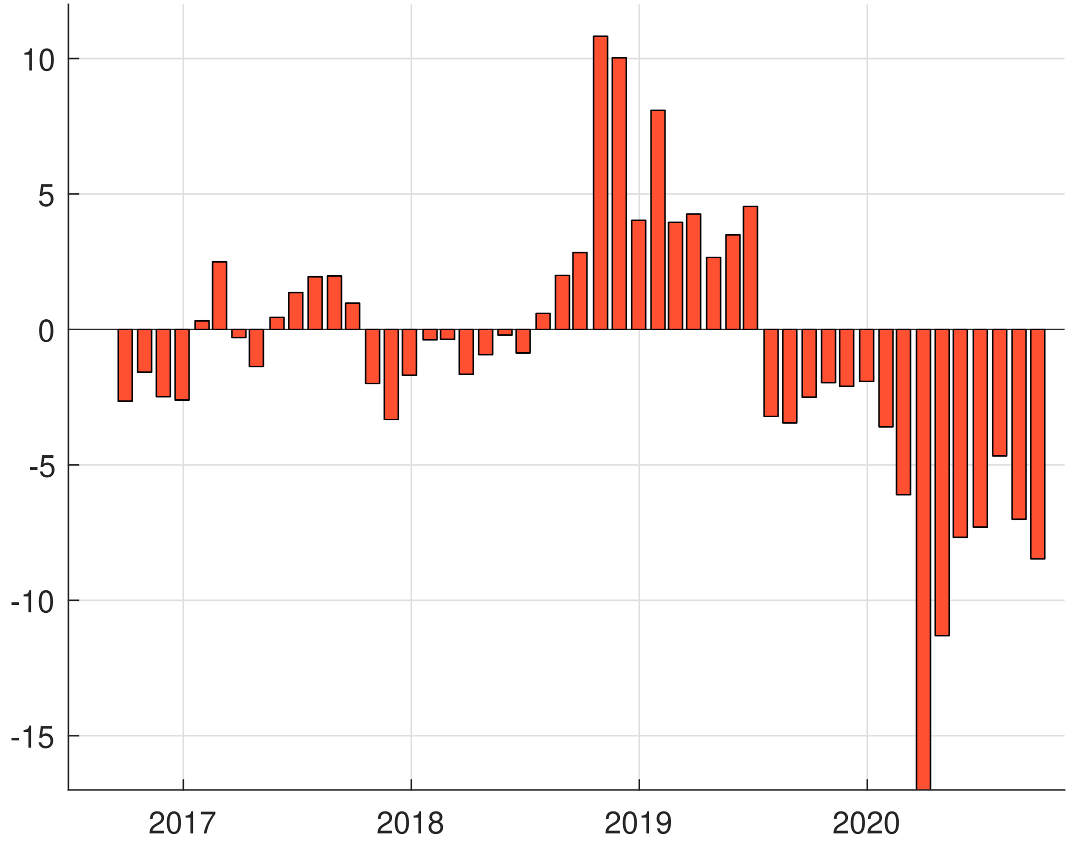


Figure 78: Evolution of the USD greenium

Source: Ben Slimane *et al.* (2020)

The green bond premium

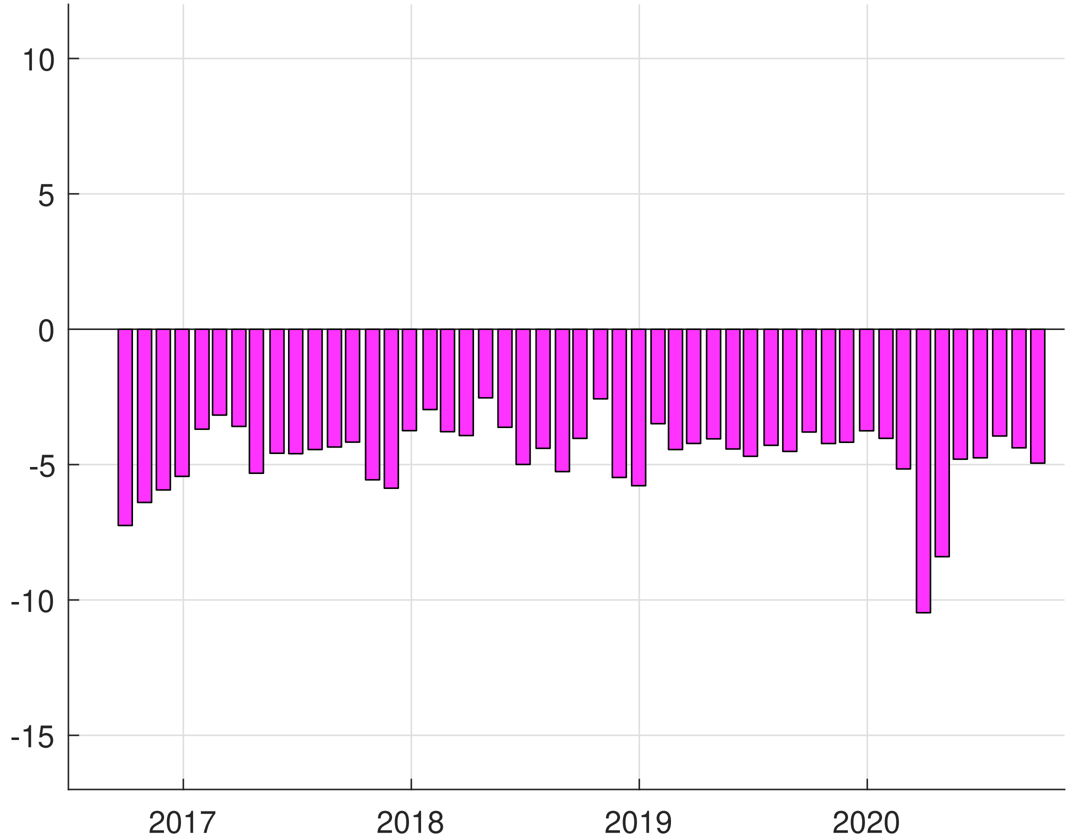


Figure 79: Evolution of the green bond premium (all currencies)

Source: Ben Slimane *et al.* (2020)

The green bond premium

Green financing $\Leftrightarrow$ green investing

1. Bond issuers have a competitive advantage to finance their environmental projects using green bonds instead of conventional bonds
2. Another premium? the “green bond issuer premium”

Social bonds

Definition

Social Bonds are any type of bond instrument where the proceeds 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 Bonds Principles (SBP).

Source: ICMA (2020), `https://www.icmagroup.org/sustainable-finance`

Social bonds

Social Bonds Principles

Social Bonds Principles (SBP)

The 4 core components of the SBP are:

1. Use of proceeds
   1. Eligible social project categories
   2. Target populations
2. Process for project evaluation and selection
3. Management of proceeds
4. Reporting

https://www.icmagroup.org/sustainable-finance/the-principles-guidelines-and-handbooks

Social bonds

Social Bonds Principles

The **eligible social projects categories** (component 1) are:

- Affordable basic infrastructure (e.g. clean drinking water, sanitation, clean energy)
- Access to essential services (e.g. health, education)
- Affordable housing (e.g. sustainable cities)
- Employment generation (e.g. pandemic crisis)
- Food security and sustainable food systems (e.g. nutritious and sufficient food, resilient agriculture)
- Socioeconomic advancement and empowerment (e.g. income inequality, gender inequality)
- Etc.

Social bonds

Social Bonds Principles

The **target populations** (component 1) are:

- Living below the poverty line
- Excluded and/or marginalised populations/communities
- People with disabilities
- Migrants and /or displaced persons
- Undereducated
- Unemployed
- Women and/or sexual and gender minorities
- Aging populations and vulnerable youth
- Etc.

Social bonds

Social Bonds Principles

With respect to the **process for project evaluation and selection** (component 2), the issuer of a social bond should clearly communicate:

- the social objectives
- the eligible projects
- the related eligibility criteria

The **management of proceeds** (component 3) includes:

- The tracking of the "*balance sheet*" and the allocation of funds[17]
- An external review (not mandatory but highly recommended)

[17] The proceeds should be credited to a sub-account

Social bonds

Social Bonds Principles

The **reporting** (component 4) must be based on the following pillars:

- Transparency
- Description of the projects, allocated amounts and expected impacts
- Qualitative performance indicators
- Quantitative performance measures (e.g. number of beneficiaries)

Social bonds

Examples

You can download the *Green, Social and Sustainability bonds database* at the following webpage:

https://www.icmagroup.org/sustainable-finance/green-social-and-sustainability-bonds-database

You can download the market information template of the social project "*Women's Livelihood Bond 2 (WLB 2) — Singapore*" at the following address:

https://www.icmagroup.org/Emails/icma-vcards/WLB2_Market%20Information%20Template.pdf

The social bond market

- The tremendous growth of the social bond market

  "Of the $\$1,280$ bn in cumulative sustainable fixed-income issuance, social bonds account for around 14% of the total, amounting to \$180bn [...] This overall expansion trend has intensified during the pandemic. In fact, the growth of the social bond market in 2020, i.e. +374% with respect to 2019 levels, dwarf both the green and sustainability bonds markets' expansion, respectively +37% and +100%" (Laugel and Vic-Philippe, 2020)

- The pandemic has increased the popularity of social bonds
- Investors focus more on the **S** pillar of ESG

Other sustainability-linked strategies

- Sustainable bonds
- Sustainable loans
- Green notes
- Green ABCP notes
- Financing renewables
- Green infrastructure funds
- ESG private equity funds
- Etc.

Definition

Definition

The key elements of impact investing are:

1. Intentionality
   The intention of an investor to generate a positive and measurable social and environmental impact
2. Additionality
   Fulfilling a positive impact beyond the provision of private capital
3. **Measurement**
   Being able to account for in a transparent way on the financial, social and environmental performance of investments

Source: Eurosif (2019)

The investor must be able to measure its impact from a quantitative point of view

GIIN

Figure 80: Global Impact Investing Network (GIIN)

`https://thegiin.org`

The example of social impact bonds

Social impact bond (SIB) = pay-for-success bond ($\approx$ call option)

The Peterborough SIB

- On 18 March 2010, the UK Secretary of State for Justice announced a six-year SIB pilot scheme that will see around 3 000 short term prisoners from Peterborough prison, serving less than 12 months, receiving intensive interventions both in prison and in the community
- Funding from investors will be initially used to pay for the services
- If reoffending is not reduced by at least 7.5%, the investors will receive no recompense

Measurement tools

Impact assessment and metrics

- Avoided CO_2 emissions in tons per $M invested
- Amount of clean water produced by the project
- Number of children who are less obese

Sustainable development goals (SDG)

The sustainable development goals are a collection of 17 interlinked global goals designed to be a "*blueprint to achieve a better and more sustainable future for all*"

https://sdgs.un.org

Sustainable development goals (SDG)

Figure 81: The map of sustainable development goals

Sustainable development goals (SDG)

Figure 82: Mapping the SDGs across E, S and G

Sustainable development goals (SDG)

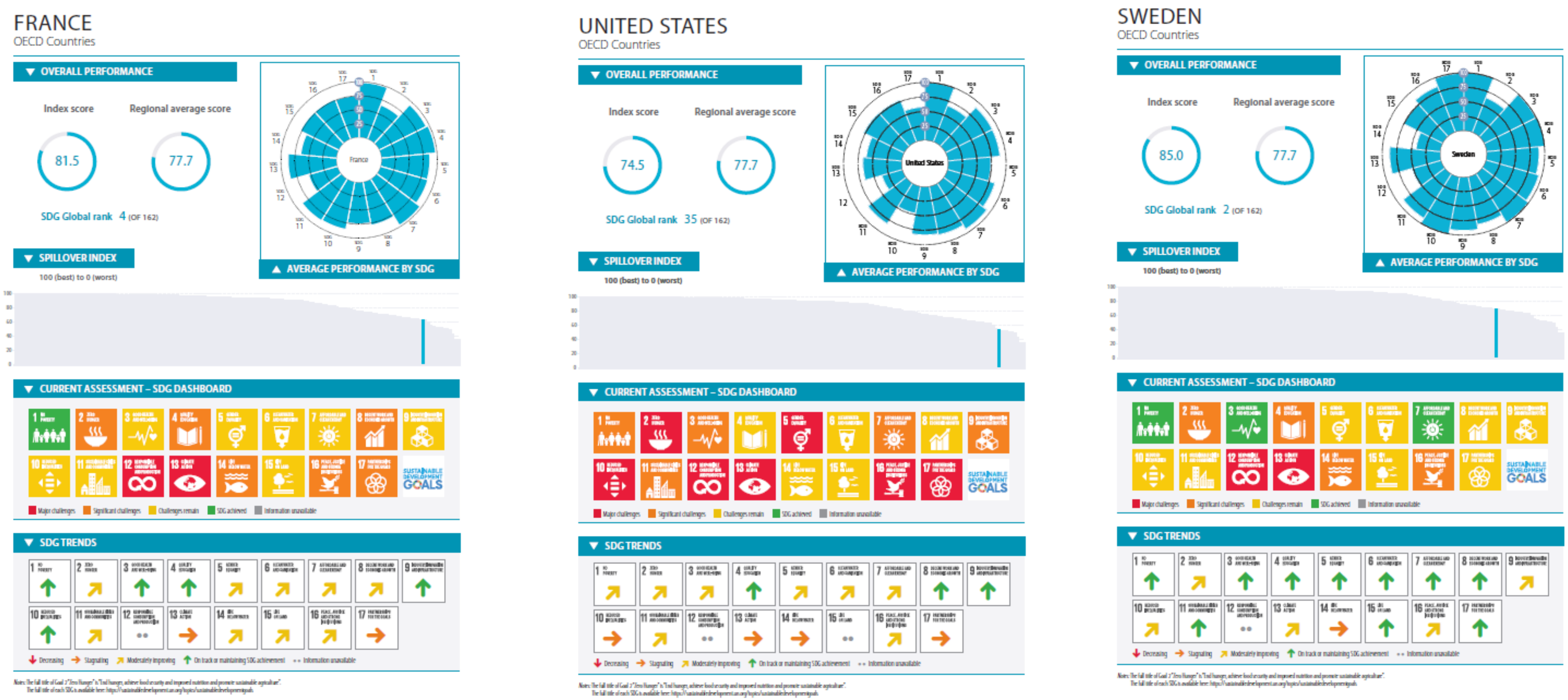


Figure 83: Examples of sovereign SDG reports

Source: Sustainable Development Report 2019, `https://dashboards.sdgindex.org`

Shareholder activism

Shareholder activism can take various forms

1. Exit (sell shares, take an offsetting bet)
2. Vote (form coalition/express dissent/call back lent shares)
3. Engage behind the scene with management and the board
4. Voice displeasure publicly (in the media)
5. Propose resolutions (shareholder proposals)
6. Initiate a takeover (acquire a sizable equity share)

Source: Bekjarovski and Brière (2018)

ESG engagement policies

- On-going engagement
  - Meet companies in order to better understand sectorial ESG challenges
  - Encourage companies to adopt best ESG practices
  - Challenge companies on ESG risks
- Engagement for influence
  - Make recommendations
  - Measure companies ESG progress
- AGM[18] engagement
  - Exercise on voting rights
  - Discuss with companies any resolution items that the investor may vote against

[18] Annual General Meeting

The challenge of reporting

- Impact reporting and investment standards (IRIS) proposed by GIIN
- EU taxonomy on sustainable finance
- Non-financial reporting directive 2014/95/EU (NFRD)
- Carbon accounting

Main references I

- Bennani, L., Le Guenedal, T., Lepetit, F., Ly, L., Mortier, V., Roncalli, T., and Sekine, T. (2018)
  How ESG Investing Has Impacted the Asset Pricing in the Equity Market, Amundi Discussion Paper, DP-39-2018, www.research-center.amundi.com.

- Bouchet, V., and Le Guenedal, T. (2020)
  Credit Risk Sensitivity to Carbon Price, *SSRN*, https://www.ssrn.com/abstract=3574486.

- Eurosif (2019)
  European SRI Study 2018, http://www.eurosif.org.

- GSIA (2019)
  Global Sustainable Investment Review 2018, http://www.gsi-alliance.org.

Main references II

LAUGEL, E., and VIC-PHILIPPE, I. (2020)
Social Bonds: Financing the Recovery and Long-Term Inclusive Growth, *Amundi Insights Paper*, www.research-center.amundi.com.

LE GUENEDAL, T. (2019)
Economic Modeling of Climate Risks, *Amundi Working Paper*, WP-83-2019, www.research-center.amundi.com.

RONCALLI, T., LE GUENEDAL, T., LEPETIT, F., RONCALLI, T., and SEKINE, T. (2020)
Measuring and Managing Carbon Risk in Investment Portfolios, *Amundi Working Paper*, WP-99-2020, www.research-center.amundi.com.

References I

Andersson, M., Bolton, P., and Samama, F. (2016)
Hedging Climate Risk, *Financial Analysts Journal*, 72(3), pp. 13-32.

Bekjarovski, F., and Brière, M. (2018)
Shareholder Activism: Why Should Investors Care?, *Amundi Discussion Paper*, DP-30-2018, www.research-center.amundi.com.

Ben Slimane, M., Da Fonseca, D., and Mahtani, V. (2020)
Facts and Fantasies About the Green Bond Premium, *Amundi Working Paper*, WP-102-2020, www.research-center.amundi.com.

Ben Slimane, M., Le Guenedal, T., Roncalli, T., and Sekine, T. (2020)
ESG Investing in Corporate Bonds: Mind the Gap, *Amundi Working Paper*, WP-94-2019, www.research-center.amundi.com.

References II

Ben Slimane, M., Brard, E., Le Guenedal, T., Roncalli, T., and Sekine, T. (2020)
ESG Investing in Fixed Income: It's Time To Cross the Rubicon, *Amundi Discussion Paper*, DP-45-2019, www.research-center.amundi.com.

Bolton, P., Despres, M., Pereira Da Silva, L.A., Samama, F. and Svartzman, R. (2020)
The Green Swan — Central Banking and Financial Stability in the Age of Climate Change, BIS Publication, https://www.bis.org/publ/othp31.htm.

Climate Bonds Initiative — CBI (2019)
Climate Bonds Standard — Version 3.0, December 2019

References III

- Cooper, C., Graham, C., and Himick, D. (2016)
  Social Impact Bonds: The Securitization of the Homeless, *Accounting, Organizations and Society*, 55, pp. 63-82.
- Drei, A., Le Guenedal, T., Lepetit, F., Mortier, V., Roncalli, T., and Sekine, T. (2020)
  ESG Investing in Recent Years: New Insights from Old Challenges, *Amundi Discussion Paper*, DP-42-2019, www.research-center.amundi.com.
- Freeman, R.E. (2010)
  Strategic Management: A Stakeholder Approach, Cambridge University Press.

References IV

FRIEDMAN, M. (2007)
The Social Responsibility of Business Is to Increase Its Profits, in Zimmerli, W.C., Holzinger, M., and Richter, K. (Eds), *Corporate Ethics and Corporate Governance*, Springer, pp. 173-178 (written in 1970 for the New York Times).

GÖRGEN, M., JACOB, A., NERLINGER, M., RIORDAN, R., ROHLEDER, M., and WILKENS, M. (2019)
Carbon Risk, *SSRN*, https://www.ssrn.com/abstract=2930897.

GSIA (2017)
Global Sustainable Investment Review 2016, http://www.gsi-alliance.org.

International Capital Market Association — ICMA (2020)
Social Bond Principles — Voluntary Process Guidelines for Issuing Social Bonds, June 2020.

References V

International Capital Market Association — ICMA (2018)
Geen Bond Principles — Voluntary Process Guidelines for Issuing Social Bonds, June 2018.

Le Guenedal, T., Girault, J., Jouanneau, M., Lepetit, F., and Sekine, T. (2020)
Trajectory Monitoring in Portfolio Management and Issuer intentionality Scoring, *Amundi Working Paper*, 97, `www.research-center.amundi.com`.

MSCI (2020)
MSCI ESG Ratings Methodology, MSCI ESG Research, April 2020.

Nordhaus, W.D. (1993)
Rolling the DICE: An Optimal Transition Path for Controlling Greenhouse, *Resource and Energy Economics*, 15, pp. 27-50.

References VI

O'Neill, B.C., Kriegler, E., Ebi, K.L., *et al.* (2017)
The Roads Ahead: Narratives for Shared Socioeconomic Pathways Describing World Futures in the 21st Century, *Global Environmental Change*, 42, pp. 169-180.

Pindyck, R.S. (2017)
The Use and Misuse of Models for Climate Policy, *Review of Environmental Economics and Policy*, 11(1), pp. 100-114.

Roncalli, T. (2017)
ESG & Factor Investing: A New Stage Has Been Reached, *Amundi ViewPoint*, `www.research-center.amundi.com`.

References VII

RONCALLI, T., LE GUENEDAL, T., LEPETIT, F., RONCALLI, T., and SEKINE, T. (2021)
The Market Measure of Carbon Risk and its Impact on the Minimum Variance Portfolio, *Amundi Working Paper*, WP-105-2021, www.research-center.amundi.com.

SO, I., and STASKEVICIUS, A. (2015)
Measuring the 'Impact' in Impact Investing, *Harvard Business School Report*.

STERN, N. (2007)
The Economics of Climate Change: The Stern Review, Cambridge University Press.

TORTORICE, D.L., BLOOM, D.E., KIRBY, P., and REGAN, J. (2020)
A Theory of Social Impact Bonds, *NBER Working Paper*, w27527.

Tutorial Exercises

Tutorial exercise 1

Probability distribution of an ESG score

Question 1

We consider an investment universe of 8 issuers with the following ESG scores:

Issuer	#1	#2	#3	#4	#5	#6	#7	#8
E	-2.80	-1.80	-1.75	0.60	0.75	1.30	1.90	2.70
S	-1.70	-1.90	0.75	-1.60	1.85	1.05	0.90	0.70
G	0.30	-0.70	-2.75	2.60	0.45	2.35	2.20	1.70

Tutorial exercise 1

Probability distribution of an ESG score

Question 1.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.

Tutorial exercise 1

Probability distribution of an ESG score

- We have:

$$s_i^{(\mathrm{ESG})} = 0.4 \times s_i^{(\mathrm{E})} + 0.4 \times s_i^{(\mathrm{S})} + 0.2 \times s_i^{(\mathrm{G})}$$

- We obtain the following results:

Issuer	#1	#2	#3	#4	#5	#6	#7	#8
$s_i^{(\mathrm{E})}$	−2.80	−1.80	−1.75	0.60	0.75	1.30	1.90	2.70
$s_i^{(\mathrm{S})}$	−1.70	−1.90	0.75	−1.60	1.85	1.05	0.90	0.70
$s_i^{(\mathrm{G})}$	0.30	−0.70	−2.75	2.60	0.45	2.35	2.20	1.70
$s_i^{(\mathrm{ESG})}$	−1.74	−1.62	−0.95	0.12	1.13	1.41	1.56	1.70

Tutorial exercise 1

Probability distribution of an ESG score

Question 1.b

Calculate the ESG score of the equally-weighted portfolio x_{ew}.

Tutorial exercise 1

Probability distribution of an ESG score

- We obtain:

$$\begin{aligned} \mathcal{S}^{(\mathrm{ESG})}\left(x_{\mathrm{ew}}\right) &= \sum_{i=1}^{8} x_{\mathrm{ew},i} \times \mathcal{S}_i^{(\mathrm{ESG})} \\ &= 0.2013 \end{aligned}$$

Tutorial exercise 1

Probability distribution of an ESG score

Question 2

We assume that the ESG scores are *iid* and follow a standard Gaussian distribution:

$$s_i \sim \mathcal{N}(0, 1)$$

Tutorial exercise 1

Probability distribution of an ESG score

Question 2.a

We note $x_{\mathrm{ew}}^{(n)}$ the equally-weighted portfolio composed of n issuers. Calculate the distribution of the ESG score $\mathcal{S}\left(x_{\mathrm{ew}}^{(n)}\right)$ of the portfolio $x_{\mathrm{ew}}^{(n)}$.

Tutorial exercise 1

Probability distribution of an ESG score

- We have:

$$\begin{aligned} \mathcal{S}\left(x_{\mathrm{ew}}^{(n)}\right) &= \sum_{i=1}^{n} x_{\mathrm{ew},i}^{(n)} \times \mathcal{S}_i \\ &= \frac{1}{n}\sum_{i=1}^{n} \mathcal{S}_i \end{aligned}$$

We deduce that $\mathcal{S}\left(x_{\mathrm{ew}}^{(n)}\right)$ follows a Gaussian distribution.

Tutorial exercise 1

Probability distribution of an ESG score

- Its mean is equal to:

$$\mathbb{E}\left[\mathcal{S}\left(x_{\mathrm{ew}}^{(n)}\right)\right] = \frac{1}{n}\sum_{i=1}^{n}\mathbb{E}\left[\mathcal{S}_i\right] = 0$$

- Its standard deviation is equal to:

$$\begin{aligned}\sigma\left(\mathcal{S}\left(x_{\mathrm{ew}}^{(n)}\right)\right) &= \sqrt{\frac{1}{n^2}\sum_{i=1}^{n}\sigma^2\left(\mathcal{S}_i\right)} \\ &= \frac{1}{\sqrt{n}}\end{aligned}$$

- Finally, we obtain:

$$\mathcal{S}\left(x_{\mathrm{ew}}^{(n)}\right) \sim \mathcal{N}\left(0, \frac{1}{n}\right)$$

Tutorial exercise 1

Probability distribution of an ESG score

Question 2.b

What is the ESG score of a well-diversified portfolio?

Tutorial exercise 1

Probability distribution of an ESG score

- The behavior of a well-diversified portfolio is close to an equally-weighted portfolio with n sufficiently large. Therefore, the ESG score is close to zero because we have:

$$\lim_{n \to \infty} \mathcal{S}\left(x_{\mathrm{ew}}^{(n)}\right) = 0$$

Tutorial exercise 1

Probability distribution of an ESG score

Question 2.c

We note $T \sim \mathbf{F}_{\alpha}$ where $\mathbf{F}_{\alpha}(t) = t^{\alpha}$, $t \in [0,1]$ and $\alpha \geq 0$. Draw the graph of the probability density function $f_{\alpha}(t)$ when α is respectively equal to 0.5, 1.5, 2.5 and 70. What do you notice?

Tutorial exercise 1

Probability distribution of an ESG score

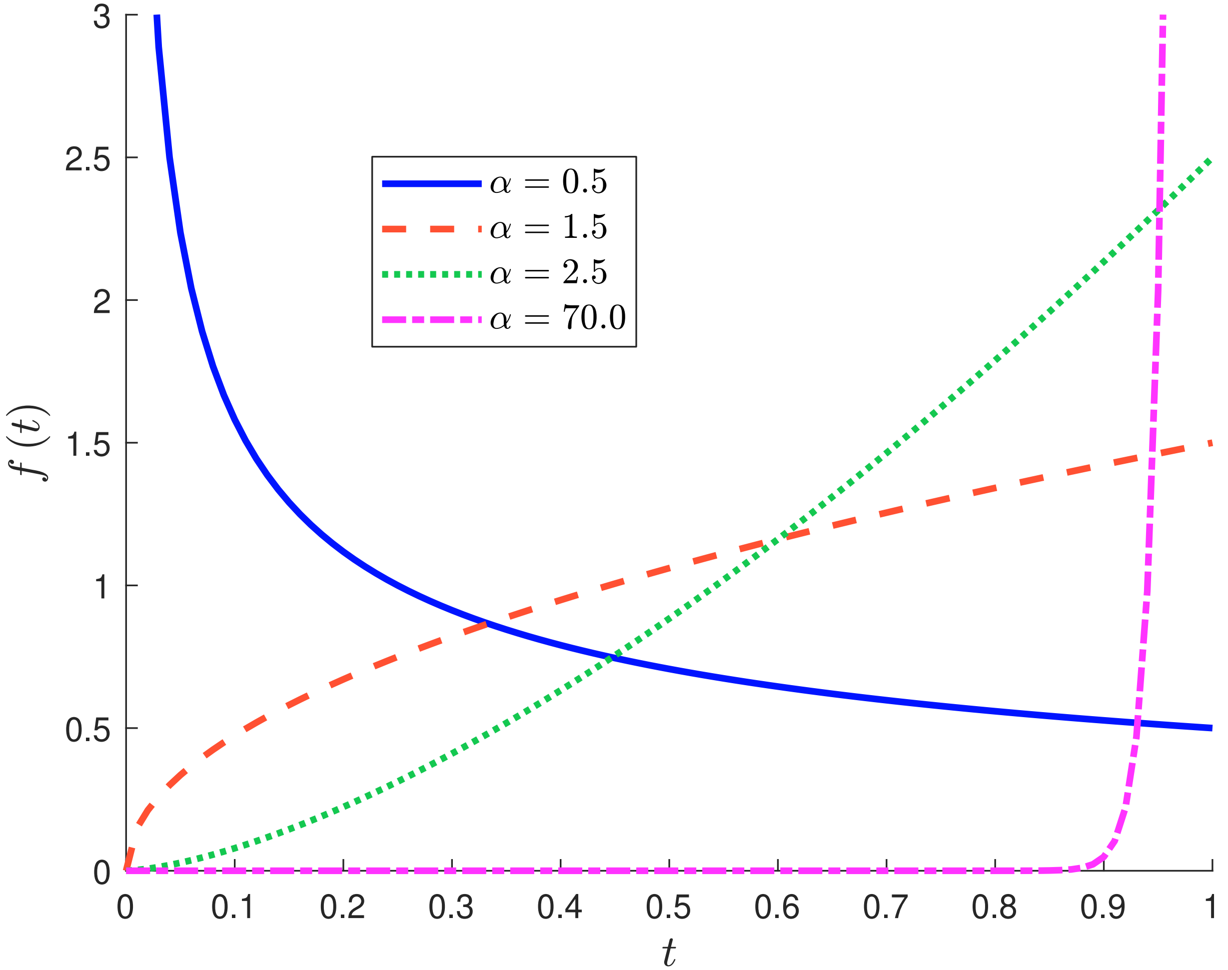


Figure 84: Probability density function $f_\alpha(t)$

Tutorial exercise 1

Probability distribution of an ESG score

- We have:

$$f_{\alpha}(t) = \alpha t^{\alpha - 1}$$

- We notice that the function $f_{\alpha}(t)$ tends to the dirac delta function when α tends to infinity:

$$\lim_{\alpha \to \infty} f_{\alpha}(t) = \delta_1(t) = \begin{cases} 0 & \text{if } t \neq 1 \\ +\infty & \text{if } t = 1 \end{cases}$$

Tutorial exercise 1

Probability distribution of an ESG score

Question 2.d

We assume that the weights of the portfolio $x = (x_1, \ldots, x_n)$ follow a power-law distribution $\mathbf{F}_\alpha$:

$$x_i \sim cT_i$$

where $T_i \sim \mathbf{F}_\alpha$ 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 α. Comment on these results. Deduce the relationship between the Herfindahl index $\mathcal{H}_\alpha(x)$ of the portfolio weights x and the parameter α.

Remark

We use $n = 50$ in the rest of the exercise.

Tutorial exercise 1

Probability distribution of an ESG score

- To simulate T_i, we use the property of the probability integral transform:

$$U_i = \mathbf{F}_\alpha \left(T_i \right) \sim \mathcal{U}_{[0,1]}$$

We deduce that:

$$\begin{aligned} T_i &= \mathbf{F}_\alpha^{-1} \left(U_i \right) \\ &= U_i^{1/\alpha} \end{aligned}$$

Tutorial exercise 1

Probability distribution of an ESG score

The algorithm for simulating the portfolio x is then the following:

1. We simulate n independent uniform random numbers $(u_1, \ldots, u_n)$.
2. We compute the random variates $(t_1, \ldots, t_n)$ where:
$$t_i = u_i^{1/\alpha}$$
3. We calculate the normalization constant:
$$c = \left(\sum_{i=1}^{n} t_i \right)^{-1} = \left(\sum_{i=1}^{n} u_i^{1/\alpha} \right)^{-1}$$
4. We deduce the portfolio weights $x = (x_1, \ldots, x_n)$:
$$x_i = c \cdot t_i = c \cdot u_i^{1/\alpha} = \frac{u_i^{1/\alpha}}{\sum_{j=1}^{n} u_j^{1/\alpha}}$$

Tutorial exercise 1

Probability distribution of an ESG score

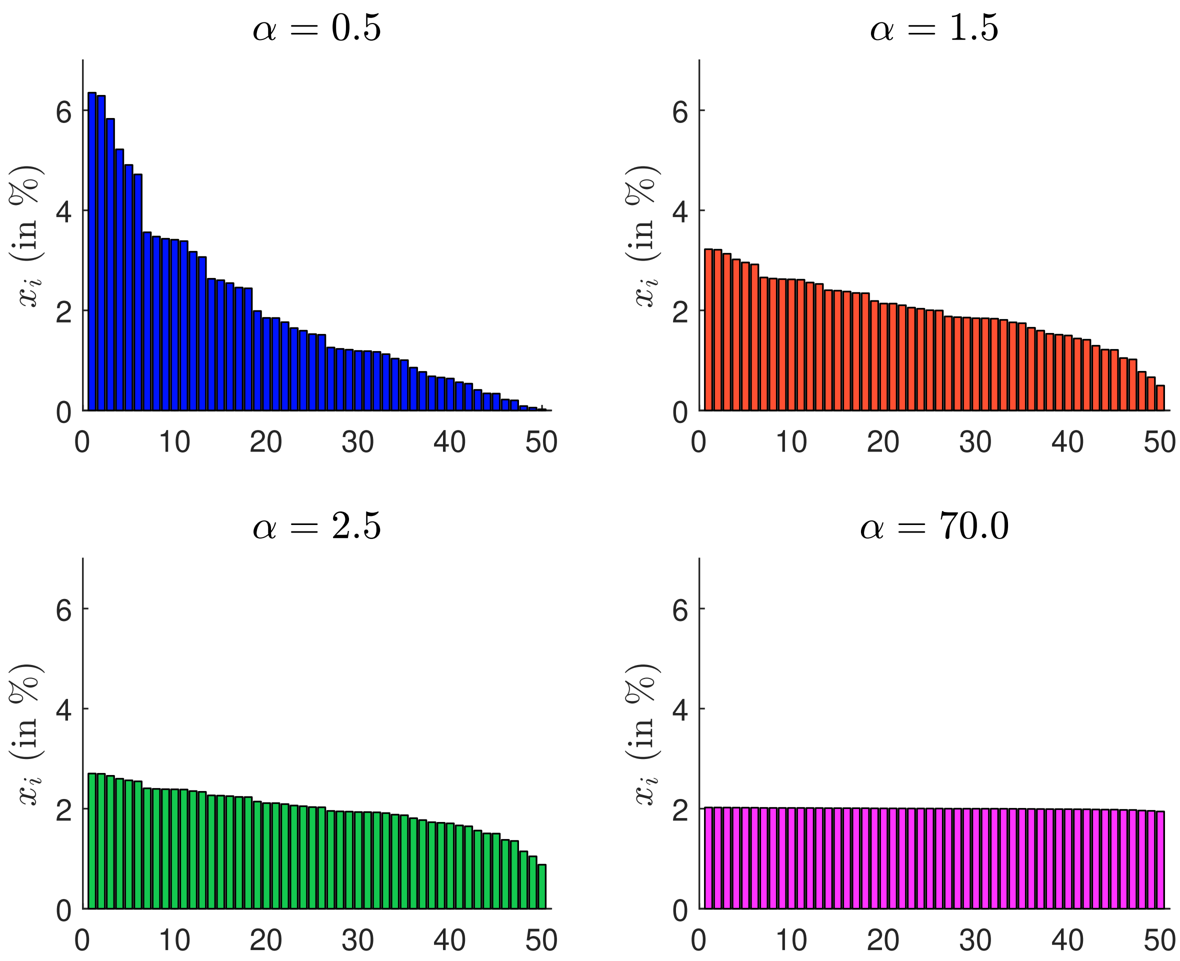


Figure 85: Repartition of the portfolio weights in descending order

Tutorial exercise 1

Probability distribution of an ESG score

- In Figure 85, we have represented the composition of the portfolio x for the 4 values of α. The weights are ranked in descending order. We deduce that the portfolio x is uniform when $\alpha \to \infty$. The parameter α controls the concentration of the portfolio. Indeed, when α is small, the portfolio is highly concentrated. It follows that the Herfindahl index $\mathcal{H}_{\alpha}(x)$ of the portfolio weights is a decreasing function of the parameter α.

Tutorial exercise 1

Probability distribution of an ESG score

Question 2.e

We assume that the weight x_i and the ESG score $\mathcal{S}_i$ of the issuer i are independent. How to simulate the portfolio ESG score $\mathcal{S}(x)$? Using 50 000 replications, estimate the probability distribution function of $\mathcal{S}(x)$ by the Monte Carlo method. Comment on these results.

Tutorial exercise 1

Probability distribution of an ESG score

- We simulate $x = (x_1, \ldots, x_n)$ using the previous algorithm. The vector of ESG scores $\mathcal{S} = (\mathcal{S}_1, \ldots, \mathcal{S}_n)$ is generated with normally-distributed random variables since we have $\mathcal{S}_i \sim \mathcal{N}(0, 1)$. We deduce that the simulated value of the portfolio ESG score $\mathcal{S}(x)$ is equal to:

$$\mathcal{S}(x) = \sum_{i=1}^{n} x_i \cdot \mathcal{S}_i$$

- We replicate the simulation of $\mathcal{S}(x)$ 50 000 times and draw the corresponding histogram in Figure 86. We also report the fitted Gaussian distribution. We observe that the portfolio ESG score $\mathcal{S}(x)$ is equal to zero on average, and its variance is an increasing function of the portfolio concentration.

Tutorial exercise 1

Probability distribution of an ESG score

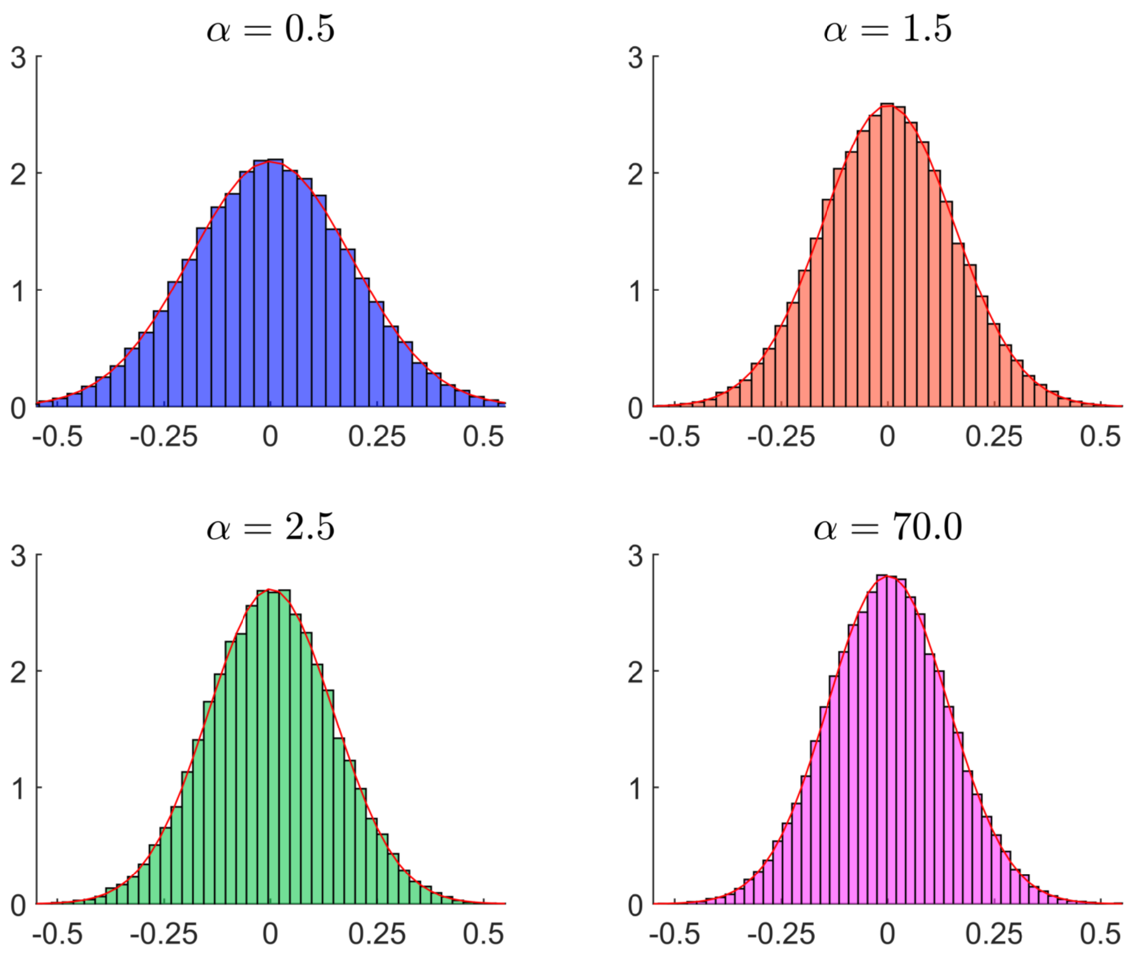


Figure 86: Histogram of the portfolio ESG score $s(x)$

Tutorial exercise 1

Probability distribution of an ESG score

Question 2.f

We now assume that the weight x_i and the ESG score $\mathcal{S}_i$ of the issuer i are positively correlated. More precisely, the dependence function between x_i and $\mathcal{S}_i$ is the Normal copula function with parameter ρ. Show that this is also the copula function between T_i and $\mathcal{S}_i$. Deduce an algorithm to simulate $\mathcal{S}(x)$.

Tutorial exercise 1

Probability distribution of an ESG score

- Since $x_i \sim c\mathcal{T}_i$, x_i is an increasing function of $\mathcal{T}_i$. We deduce that the copula function of $(\mathcal{T}_i, \mathcal{S}_i)$ is the same as the copula function of $(x_i, \mathcal{S}_i)$.
- To simulate the Normal copula function $\mathbf{C}(u, v)$, we use the transformation algorithm based on the Cholesky decomposition:

$$\left\{ \begin{array}{l} u_i = \Phi\left(g_i'\right) \\ v_i = \Phi\left(\rho g_i' + \sqrt{1-\rho^2} g_i''\right) \end{array} \right.$$

where g_i' and g_i'' are two independent random numbers from the probability distribution $\mathcal{N}(0,1)$.

Tutorial exercise 1

Probability distribution of an ESG score

Here is the algorithm to simulate the ESG portfolio score $\mathcal{S}(x)$:

1. We simulate n independent normally-distributed random numbers g_i' and g_i'' and we compute (u_i, v_i):
$$\begin{cases} u_i = \Phi(g_i') \\ v_i = \Phi\left(\rho g_i' + \sqrt{1-\rho^2} g_i''\right) \end{cases}$$
2. We compute the random variates $(t_1, \ldots, t_n)$ where $t_i = u_i^{1/\alpha}$
3. We deduce the vector of weights $x = (x_1, \ldots, x_n)$:
$$x_i = t_i \Big/ \sum_{j=1}^n t_j$$
4. We simulate the vector of scores $\mathcal{S} = (\mathcal{S}_1, \ldots, \mathcal{S}_n)$:
$$\mathcal{S}_i = \Phi^{-1}(v_i) = \rho g_i' + \sqrt{1-\rho^2} g_i''$$
5. We calculate the portfolio score:
$$\mathcal{S}(x) = \sum_{i=1}^n x_i \cdot \mathcal{S}_i$$

Tutorial exercise 1

Probability distribution of an ESG score

Question 2.g

Using 50 000 replications, estimate the probability distribution function of $s(x)$ by the Monte Carlo method when the correlation parameter ρ is set to 50%. Comment on these results.

Tutorial exercise 1

Probability distribution of an ESG score

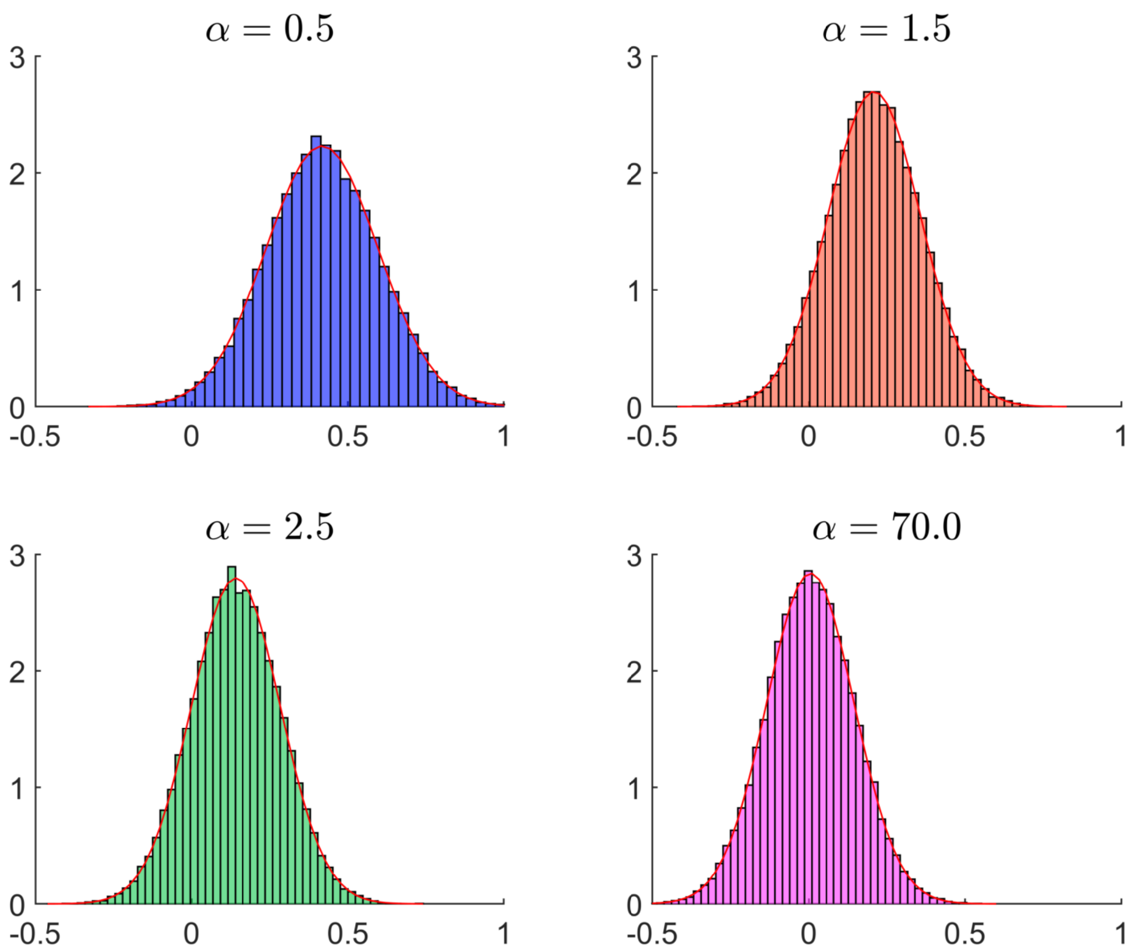


Figure 87: Histogram of the portfolio ESG score $\mathcal{S}(x)$ ($\rho = 50\%$)

Tutorial exercise 1

Probability distribution of an ESG score

- In the independent case, we found that $\mathbb{E}[s(x)] = 0$. In Figure 87, we notice that $\mathbb{E}[s(x)] \neq 0$ when ρ is equal to 50%. Indeed, we obtain:

$$\mathbb{E}[s(x)] = \begin{cases} 0.418 & \text{if } \alpha = 0.5 \\ 0.210 & \text{if } \alpha = 1.5 \\ 0.142 & \text{if } \alpha = 2.5 \\ 0.006 & \text{if } \alpha = 70.0 \end{cases}$$

Tutorial exercise 1

Probability distribution of an ESG score

Question 2.h

Estimate the relationship between the correlation parameter ρ and the expected ESG score $\mathbb{E}[s(x)]$ of the portfolio x. Comment on these results.

Tutorial exercise 1

Probability distribution of an ESG score

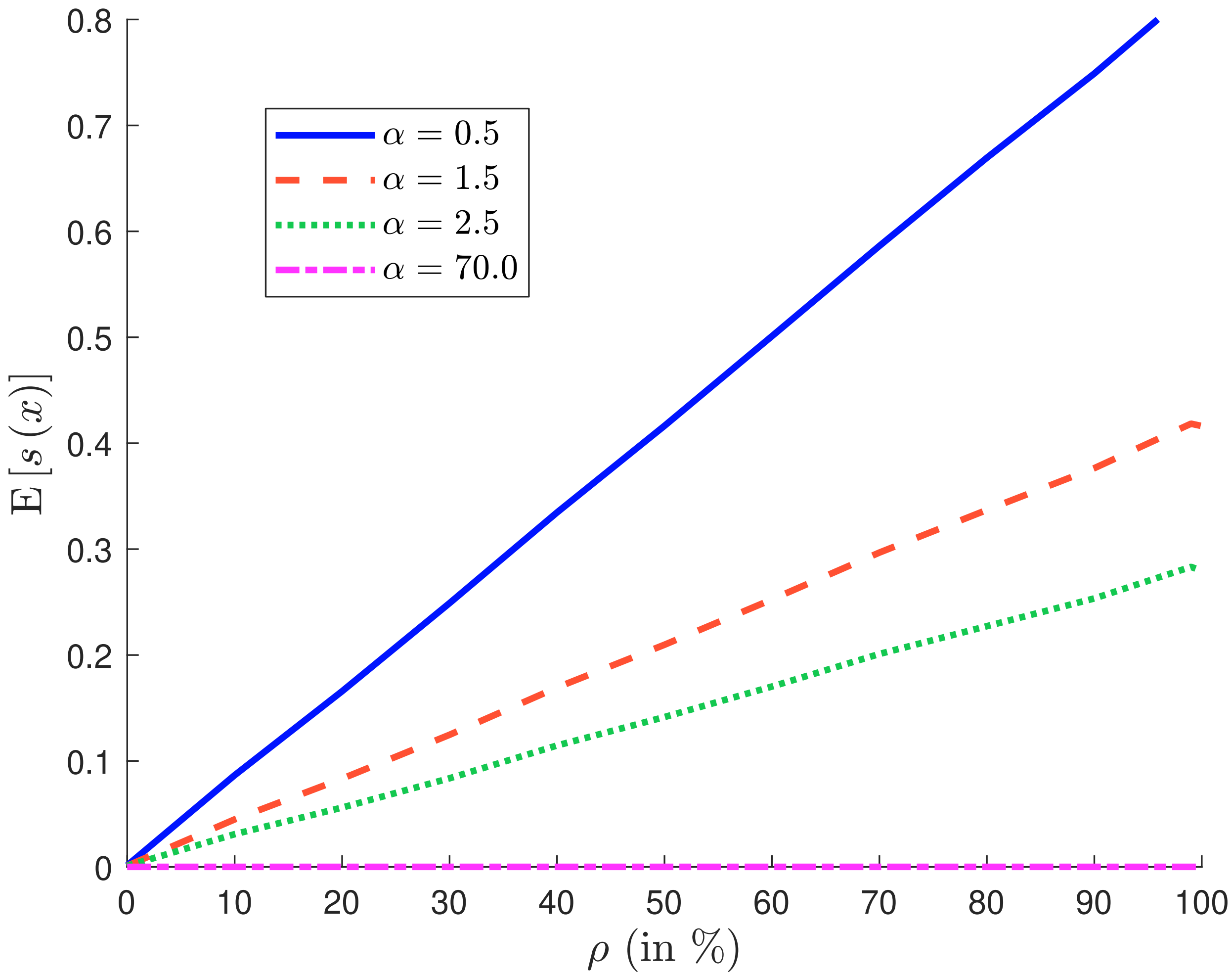


Figure 88: Relationship between ρ and $\mathbb{E}[s(x)]$

Tutorial exercise 1

Probability distribution of an ESG score

- We notice that there is a positive relationship between ρ and $\mathbb{E}\left[\mathcal{S}\left(x\right)\right]$ and the slope increases with the concentration of the portfolio.

Tutorial exercise 1

Probability distribution of an ESG score

Question 2.i

How are the previous results related to the size bias of ESG scoring?

Tutorial exercise 1

Probability distribution of an ESG score

- Big cap companies have more (financial and human) resources to develop an ESG policy than small cap companies.
- Therefore, we observe a positive correlation between the market capitalization and the ESG score of an issuer.
- It follows that ESG portfolios have generally a size bias. For instance, we generally observe that cap-weighted indexes have an ESG score which is greater than the average of ESG scores.
- In the previous questions, we verify that $\mathbb{E}[\mathcal{S}(x)] \geq \mathbb{E}[\mathcal{S}]$ when the Herfindahl index of the portfolio x is high and the correlation between x_i and $\mathcal{S}_i$ is positive.

Tutorial exercise 1

Probability distribution of an ESG score

Question 3

Let $\mathcal{S}$ be the ESG score of the issuer. We assume that the ESG score follows a standard Gaussian distribution:

$$\mathcal{S} \sim \mathcal{N}(0, 1)$$

The ESG score $\mathcal{S}$ is also converted into an ESG rating $\mathcal{R}$, which can take the values **A**, **B**, **C** and **D** — **A** is the best rating and **D** is the worst rating.

Tutorial exercise 1

Probability distribution of an ESG score

Question 3.a

We assume that the breakpoints of the rating system are -1.5, 0 and $+1.5$. Compute the frequencies of the ratings.

Tutorial exercise 1

Probability distribution of an ESG score

- We have:

$$\begin{aligned} \Pr\{\mathcal{R} = \mathbf{A}\} &= \Pr\{\mathcal{s} \geq 1.5\} \\ &= 1 - \Phi(1.5) \\ &= 6.68\% \end{aligned}$$

and:

$$\begin{aligned} \Pr\{\mathcal{R} = \mathbf{B}\} &= \Pr\{0 \leq \mathcal{s} < 1.5\} \\ &= \Phi(1.5) - \Phi(0) \\ &= 43.32\% \end{aligned}$$

- Since the Gaussian distribution is symmetric around 0, we also have:

$$\Pr\{\mathcal{R} = \mathbf{C}\} = \Pr\{\mathcal{R} = \mathbf{B}\} = 43.32\%$$

and:

$$\Pr\{\mathcal{R} = \mathbf{D}\} = \Pr\{\mathcal{R} = \mathbf{A}\} = 6.68\%$$

Tutorial exercise 1

Probability distribution of an ESG score

- The mapping function is:

$$\mathcal{M}_{\text{appring}}(s) = \begin{cases} \mathbf{A} & \text{if } s < -1.5 \\ \mathbf{B} & \text{if } -1.5 \leq s < 0 \\ \mathbf{C} & \text{if } 0 \leq s < 1.5 \\ \mathbf{D} & \text{if } s \geq 1.5 \end{cases}$$

Tutorial exercise 1

Probability distribution of an ESG score

Question 3.b

We would like to build a rating system such that each category has the same frequency. Find the mapping function.

Tutorial exercise 1

Probability distribution of an ESG score

- We have:

  $$\Pr\{\mathcal{R}(t) = \mathbf{A}\} = \Pr\{\mathcal{R}(t) = \mathbf{B}\} = \Pr\{\mathcal{R}(t) = \mathbf{C}\} = \Pr\{\mathcal{R}(t) = \mathbf{D}\}$$

  and:

  $$\Pr\{\mathcal{R}(t) = \mathbf{A}\}+\Pr\{\mathcal{R}(t) = \mathbf{B}\}+\Pr\{\mathcal{R}(t) = \mathbf{C}\}+\Pr\{\mathcal{R}(t) = \mathbf{D}\} = 1$$

  We deduce that:

  $$\Pr\{\mathcal{R}(t) = \mathbf{A}\} = \frac{1}{4} = 25\%$$

  and $\Pr\{\mathcal{R}(t) = \mathbf{B}\} = \Pr\{\mathcal{R}(t) = \mathbf{C}\} = \Pr\{\mathcal{R}(t) = \mathbf{D}\} = 25\%$.
- We want to find the breakpoints (s_1, s_2, s_3) such that:

  $$\left\{\begin{array}{l} \Pr\{\mathcal{S} < s_1\} = 25\% \\ \Pr\{s_1 \leq \mathcal{S} < s_2\} = 25\% \\ \Pr\{s_2 \leq \mathcal{S} < s_3\} = 25\% \\ \Pr\{\mathcal{S} \geq s_3\} = 25\% \end{array}\right.$$

Tutorial exercise 1

Probability distribution of an ESG score

- We deduce that:

$$\left\{\begin{array}{l} s_1 = \Phi^{-1}(0.25) = -0.6745 \\ s_2 = \Phi^{-1}(0.50) = 0 \\ s_3 = \Phi^{-1}(0.75) = +0.6745 \end{array}\right.$$

- The mapping function is:

$$\mathcal{M}_{\text{appring}}(\mathcal{s}) = \left\{\begin{array}{ll} \textbf{A} & \text{if } \mathcal{s} < -0.6745 \\ \textbf{B} & \text{if } -0.6745 \leq \mathcal{s} < 0 \\ \textbf{C} & \text{if } 0 \leq \mathcal{s} < 0.6745 \\ \textbf{D} & \text{if } \mathcal{s} \geq 0.6745 \end{array}\right.$$

Tutorial exercise 1

Probability distribution of an ESG score

Question 3.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.

Tutorial exercise 1

Probability distribution of an ESG score

- We have:

$$\left\{ \begin{array}{l} s_1 = \Phi^{-1}(0.10) = -1.2816 \\ s_2 = \Phi^{-1}(0.50) = 0 \\ s_3 = \Phi^{-1}(0.90) = +1.2816 \end{array} \right.$$

- The mapping function is:

$$\mathcal{M}_{\mathrm{appring}}(s) = \left\{ \begin{array}{ll} \mathbf{A} & \text{if } s < -1.2816 \\ \mathbf{B} & \text{if } -1.2816 \leq s < 0 \\ \mathbf{C} & \text{if } 0 \leq s < 1.2816 \\ \mathbf{D} & \text{if } s \geq 1.2816 \end{array} \right.$$

Tutorial exercise 1

Probability distribution of an ESG score

Question 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:

- The ESG score at time $t-1$ follows a standard Gaussian distribution:

$$s(t-1) \sim \mathcal{N}(0,1)$$

- The variation of the ESG score is Gaussian between two months:

$$\Delta s(t) = s(t) - s(t-1) \sim \mathcal{N}(0,\sigma^2)$$

- The ESG score $s(t-1)$ and the variation $\Delta s(t)$ are independent.

Tutorial exercise 1

Probability distribution of an ESG score

Question 4

The ESG score $\mathcal{S}(t)$ is converted into an ESG rating $\mathcal{R}(t)$, which can take following grades:

$$\mathcal{R}_1 \prec \mathcal{R}_2 \prec \cdots \prec \mathcal{R}_k \prec \cdots \prec \mathcal{R}_{K-1} \prec \mathcal{R}_K$$

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 $s_K = +\infty$.

Tutorial exercise 1

Probability distribution of an ESG score

Question 4.a

Compute the bivariate probability distribution of the random vector $(s(t-1), \Delta s(t))$.

Tutorial exercise 1

Probability distribution of an ESG score

- The joint distribution of $(\mathcal{S}(t-1), \Delta\mathcal{S}(t))$ is:

$$\begin{pmatrix} \mathcal{S}(t-1) \\ \Delta\mathcal{S}(t) \end{pmatrix} \sim \mathcal{N}\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & 0 \\ 0 & \sigma^2 \end{pmatrix}\right)$$

Tutorial exercise 1

Probability distribution of an ESG score

Question 4.b

Compute the bivariate distribution of the random vector $(s(t-1), s(t))$.

Tutorial exercise 1

Probability distribution of an ESG score

- Since we have:

$$s(t) = s(t-1) + \Delta s(t)$$

we deduce that:

$$\begin{pmatrix} s(t-1) \\ s(t) \end{pmatrix} = \begin{pmatrix} 1 & 0 \\ 1 & 1 \end{pmatrix} \begin{pmatrix} s(t-1) \\ \Delta s(t) \end{pmatrix}$$

We conclude that $(s(t-1), s(t))$ is a Gaussian random vector.

Tutorial exercise 1

Probability distribution of an ESG score

- We have:

$$\operatorname{var}\left(s\left(t\right)\right) = 1 + \sigma^2$$

and:

$$\begin{aligned}
\operatorname{cov}\left(s\left(t-1\right), s\left(t\right)\right) &= \mathbb{E}\left[s\left(t-1\right) \cdot s\left(t\right)\right] \\
&= \mathbb{E}\left[s^2\left(t-1\right) + s\left(t-1\right) \cdot \Delta s\left(t\right)\right] \\
&= 1
\end{aligned}$$

Tutorial exercise 1

Probability distribution of an ESG score

- It follows that:

$$\begin{pmatrix} \mathcal{S}(t-1) \\ \mathcal{S}(t) \end{pmatrix} \sim \mathcal{N}\left(\mathbf{0}_2, \Sigma_\sigma\right)$$

where Σ_σ is the covariance matrix:

$$\Sigma_\sigma = \begin{pmatrix} 1 & 1 \\ 1 & 1+\sigma^2 \end{pmatrix}$$

Tutorial exercise 1

Probability distribution of an ESG score

Question 4.c

Compute the probability $p_k = \Pr\{\mathcal{R}(t-1) = \mathcal{R}_k\}$.

Tutorial exercise 1

Probability distribution of an ESG score

- We have:

$$\begin{aligned}
\Pr\left\{\mathcal{R}(t-1)=\mathcal{R}_k\right\} &= \Pr\left\{s_{k-1}\leq \mathcal{S}(t-1)<s_k\right\} \\
&= \Phi\left(s_k\right)-\Phi\left(s_{k-1}\right)
\end{aligned}$$

Tutorial exercise 1

Probability distribution of an ESG score

Question 4.d

Compute the joint probability $\Pr\left\{\mathcal{R}(t) = \mathcal{R}_k, \mathcal{R}(t-1) = \mathcal{R}_j\right\}$.

Tutorial exercise 1

Probability distribution of an ESG score

- We have:

$$
\begin{aligned}
(*) &= \Pr\left\{\mathcal{R}(t) = \mathcal{R}_k, \mathcal{R}(t-1) = \mathcal{R}_j\right\} \\
&= \Pr\left\{s_{k-1} \leq \mathcal{s}(t) < s_k, s_{j-1} \leq \mathcal{s}(t-1) < s_j\right\} \\
&= \Phi_2\left(s_j, s_k; \Sigma_\sigma\right) - \Phi_2\left(s_{j-1}, s_k; \Sigma_\sigma\right) - \\
&\quad\; \Phi_2\left(s_j, s_{k-1}; \Sigma_\sigma\right) + \Phi_2\left(s_{j-1}, s_{k-1}; \Sigma_\sigma\right)
\end{aligned}
$$

where $\Phi_2\left(x, y; \Sigma_\sigma\right)$ is the bivariate Normal cdf with covariance matrix Σ_σ.

Tutorial exercise 1

Probability distribution of an ESG score

Question 4.e

Compute the transition probability
$p_{j,k} = \Pr\{\mathcal{R}(t) = \mathcal{R}_k \mid \mathcal{R}(t-1) = \mathcal{R}_j\}$.

Tutorial exercise 1

Probability distribution of an ESG score

- We have:

$$\begin{aligned} p_{j,k} &= \Pr\left\{\mathcal{R}\left(t\right) = \mathcal{R}_k \mid \mathcal{R}\left(t-1\right) = \mathcal{R}_j\right\} \\ &= \frac{\Pr\left\{\mathcal{R}\left(t\right) = \mathcal{R}_k, \mathcal{R}\left(t-1\right) = \mathcal{R}_j\right\}}{\Pr\left\{\mathcal{R}\left(t-1\right) = \mathcal{R}_j\right\}} \\ &= \frac{\Phi_2\left(s_j, s_k; \Sigma_\sigma\right) + \Phi_2\left(s_{j-1}, s_{k-1}; \Sigma_\sigma\right)}{\Phi\left(s_j\right) - \Phi\left(s_{j-1}\right)} - \\ & \quad \frac{\Phi_2\left(s_{j-1}, s_k; \Sigma_\sigma\right) + \Phi_2\left(s_j, s_{k-1}; \Sigma_\sigma\right)}{\Phi\left(s_j\right) - \Phi\left(s_{j-1}\right)} \end{aligned}$$

Tutorial exercise 1

Probability distribution of an ESG score

Question 4.f

Compute the monthly turnover $\mathcal{T}(\mathcal{R}_k)$ of the ESG rating $\mathcal{R}_k$.

Tutorial exercise 1

Probability distribution of an ESG score

- We have:

$$
\begin{aligned}
\mathcal{T}(\mathcal{R}_k) &= \Pr\{\mathcal{R}(t) \neq \mathcal{R}_k \mid \mathcal{R}(t-1) = \mathcal{R}_k\} \\
&= 1 - \Pr\{\mathcal{R}(t) = \mathcal{R}_k \mid \mathcal{R}(t-1) = \mathcal{R}_k\} \\
&= 1 - p_{k,k}
\end{aligned}
$$

Tutorial exercise 1

Probability distribution of an ESG score

Question 4.g

Compute the monthly turnover $\mathcal{T}(\mathcal{R}_1, \ldots, \mathcal{R}_K)$ of the ESG rating system.

Tutorial exercise 1

Probability distribution of an ESG score

- We have:

$$
\begin{aligned}
\mathcal{T}\left(\mathcal{R}_1, \ldots, \mathcal{R}_K\right) &= \sum_{k=1}^{K} \Pr\left\{\mathcal{R}\left(t-1\right) = \mathcal{R}_k\right\} \cdot \mathcal{T}\left(\mathcal{R}_k\right) \\
&= \sum_{k=1}^{K} \Pr\left\{\mathcal{R}\left(t\right) \neq \mathcal{R}_k, \mathcal{R}\left(t-1\right) = \mathcal{R}_k\right\}
\end{aligned}
$$

Tutorial exercise 1

Probability distribution of an ESG score

Question 4.h

For each rating system given in Questions 3.a, 3.b and 3.c, determine the corresponding ESG migration matrix and the monthly turnover of the rating system if we assume that σ is equal to 10%. What is the best ESG rating system if we would like to control the turnover of ESG ratings?

Tutorial exercise 1

Probability distribution of an ESG score

Table 31: ESG rating migration matrix (Question 3.a)

Rating	s_k	p_k	Transition probability $p_{j,k}$				$\mathcal{T}(\mathcal{R}_k)$
D		6.68%	92.96%	7.04%	0.00%	0.00%	7.04%
C	-1.50	43.32%	1.31%	95.03%	3.66%	0.00%	4.97%
B	0.00	43.32%	0.00%	3.66%	95.03%	1.31%	4.97%
A	1.50	6.68%	0.00%	0.00%	7.04%	92.96%	7.04%
$\mathcal{T}(\mathcal{R}_1, \ldots, \mathcal{R}_K)$							5.25%

Tutorial exercise 1

Probability distribution of an ESG score

Table 32: ESG rating migration matrix (Question 3.b)

Rating	s_k	p_k	Transition probability $p_{j,k}$				$\mathcal{T}(\mathcal{R}_k)$
D		25.00%	95.15%	4.85%	0.00%	0.00%	4.85%
C	-0.67	25.00%	5.27%	88.38%	6.35%	0.00%	11.62%
B	0.00	25.00%	0.00%	6.35%	88.38%	5.27%	11.62%
A	0.67	25.00%	0.00%	0.00%	4.85%	95.15%	4.85%
$\mathcal{T}(\mathcal{R}_1,\ldots,\mathcal{R}_K)$							8.23%

Tutorial exercise 1

Probability distribution of an ESG score

Table 33: ESG rating migration matrix (Question 3.c)

Rating	s_k	p_k	Transition probability $p_{j,k}$				$\mathcal{T}(\mathcal{R}_k)$
D		10.00%	93.54%	6.46%	0.00%	0.00%	6.46%
	-1.28						
C		40.00%	1.89%	94.14%	3.97%	0.00%	5.86%
	0.00						
B		40.00%	0.00%	3.97%	94.14%	1.89%	5.86%
	1.28						
A		10.00%	0.00%	0.00%	6.46%	93.54%	6.46%
$\mathcal{T}(\mathcal{R}_1, \ldots, \mathcal{R}_K)$							5.98%

Tutorial exercise 1

Probability distribution of an ESG score

The ESG rating system defined in Question 3.a is the best rating system if we would like to reduce the monthly turnover of ESG ratings.

Tutorial exercise 1

Probability distribution of an ESG score

Question 4.i

Draw the relationship between the parameter σ and the turnover $\mathcal{T}(\mathcal{R}_1, \ldots, \mathcal{R}_K)$ for the three ESG rating systems.

Tutorial exercise 1

Probability distribution of an ESG score

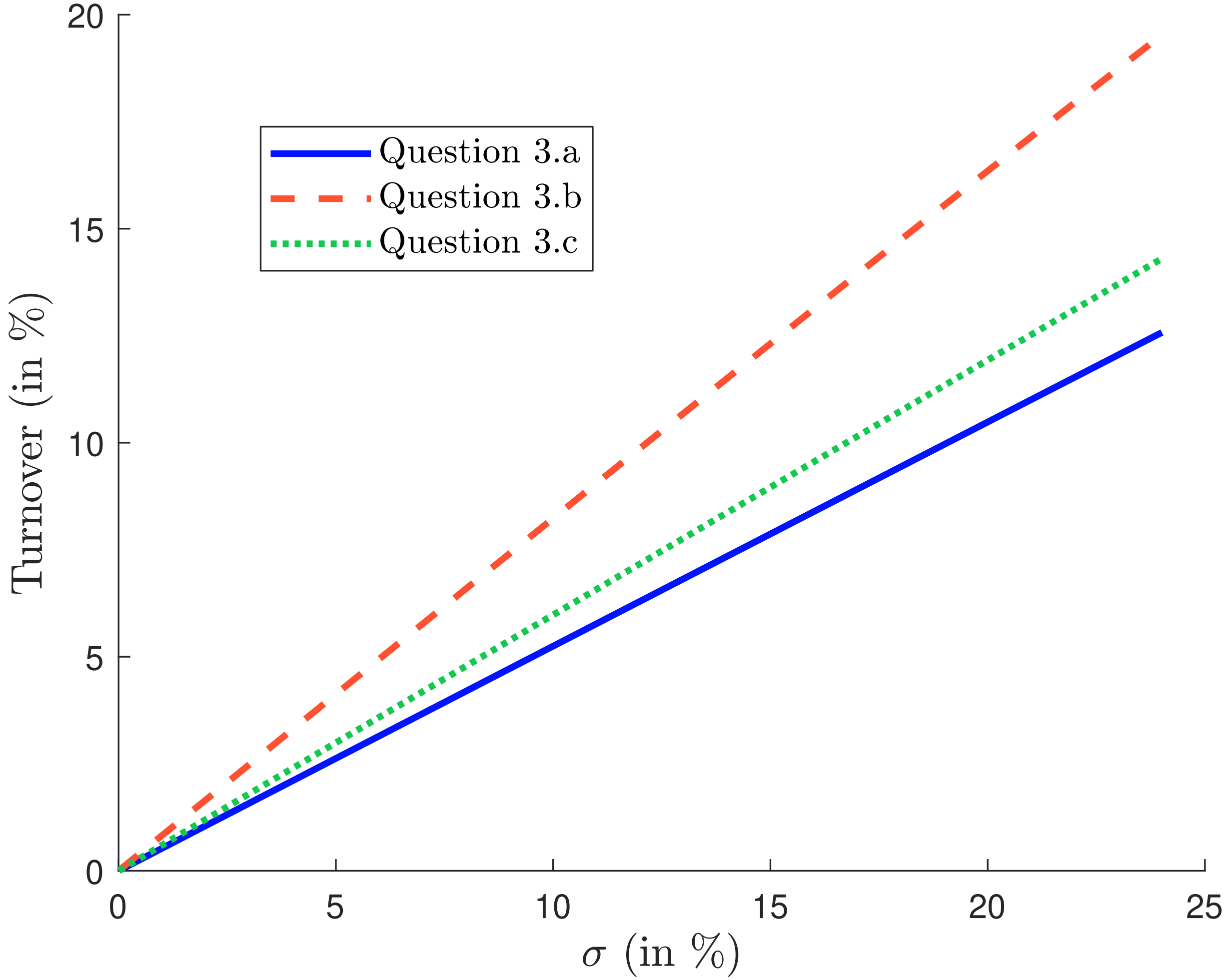


Figure 89: Relationship between σ and $\mathcal{T}(\mathcal{R}_1, \ldots, \mathcal{R}_K)$

Tutorial exercise 1

Probability distribution of an ESG score

Question 4.j

We consider a uniform ESG rating system where:

$$\Pr\left\{\mathcal{R}\left(t-1\right)=\mathcal{R}_k\right\}=\frac{1}{K}$$

Draw the relationship between the number of notches K and the turnover $\mathcal{T}\left(\mathcal{R}_1,\ldots,\mathcal{R}_K\right)$ when the parameter σ takes the values 5%, 10% and 25%.

Tutorial exercise 1

Probability distribution of an ESG score

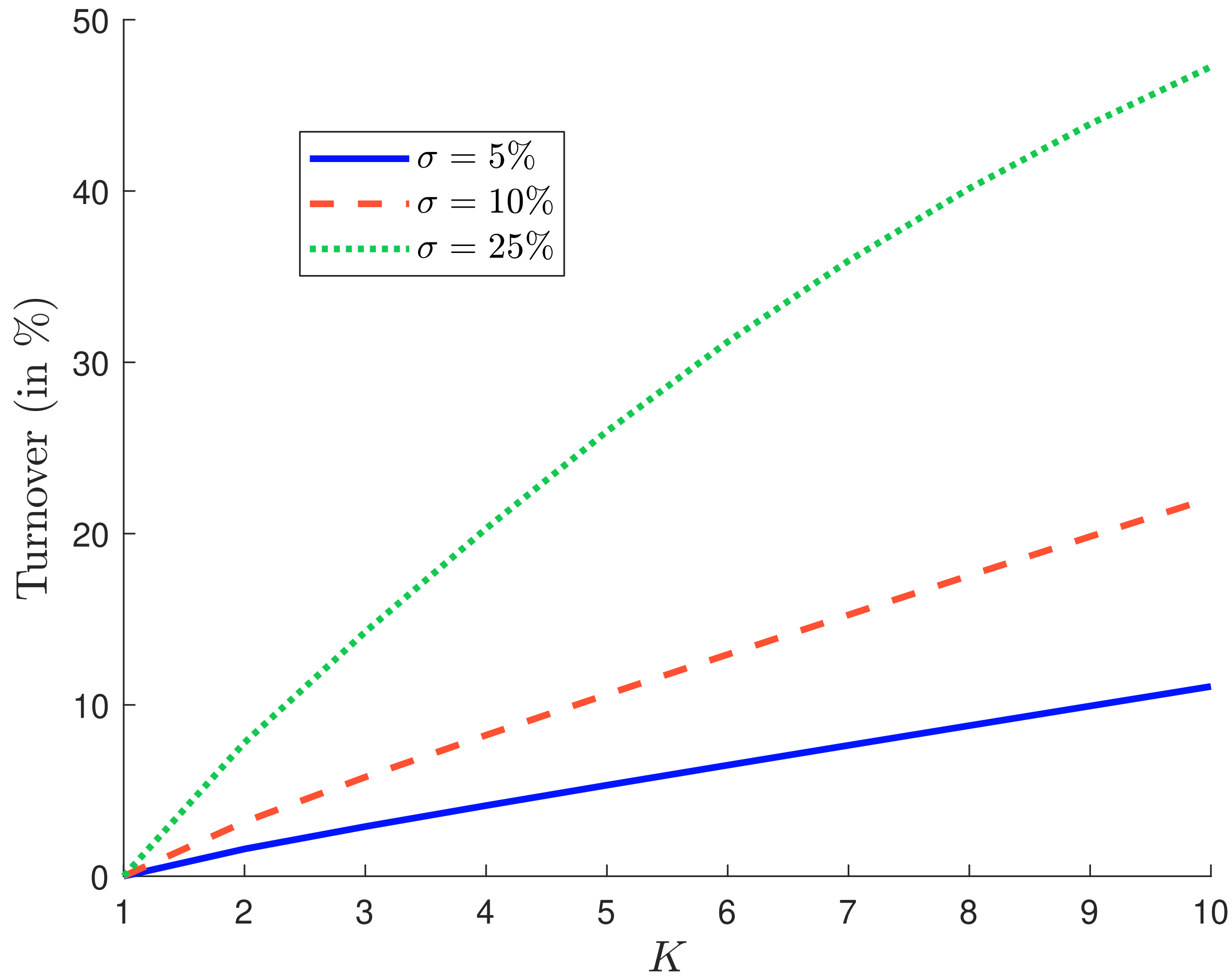


Figure 90: Relationship between K and $\mathcal{T}(\mathcal{R}_1, \ldots, \mathcal{R}_K)$

Tutorial exercise 1

Probability distribution of an ESG score

Question 4.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?

Tutorial exercise 1

Probability distribution of an ESG score

- An ESG rating system is mainly quantitative and highly depends on the mapping function. This is not the case of a credit rating system, which is mainly qualitative and discretionary.
- This explains that the turnover of an ESG rating system is higher than the turnover of a credit rating system.
- The stabilization of the ESG rating system implies to reduce the turnover $\mathcal{T}(\mathcal{R}_1, \ldots, \mathcal{R}_K)$, which depends on:
  1. The number of notches[19] K;
  2. The volatility σ of score changes
  3. The design of the ESG rating system $(s_1, \ldots, s_{K-1})$
- The turnover $\mathcal{T}(\mathcal{R}_1, \ldots, \mathcal{R}_K)$ has a big impact on an ESG exclusion (or negative screening) policy, because it creates noisy short-term entry/exit positions that do not necessarily correspond to a decrease or increase of the long-term ESG risks.

[19] This is why ESG rating systems have less notches than credit rating systems

Tutorial exercise 2

Enhanced ESG score & tracking error control

Exercise

We consider a capitalization-weighted equity index, which is composed of 8 stocks. Their weights, volatilities and ESG scores are the following:

Stock	#1	#2	#3	#4	#5	#6	#7	#8
CW weight	0.23	0.19	0.17	0.13	0.09	0.08	0.06	0.05
Volatility	0.22	0.20	0.25	0.18	0.35	0.23	0.13	0.29
ESG score	−1.20	0.80	2.75	1.60	−2.75	−1.30	0.90	−1.70

The correlation matrix is given by:

$$\rho = \begin{pmatrix}
100\% & & & & & & & \\
80\% & 100\% & & & & & & \\
70\% & 75\% & 100\% & & & & & \\
60\% & 65\% & 80\% & 100\% & & & & \\
70\% & 50\% & 70\% & 85\% & 100\% & & & \\
50\% & 60\% & 70\% & 80\% & 60\% & 100\% & & \\
70\% & 50\% & 70\% & 75\% & 80\% & 50\% & 100\% & \\
60\% & 65\% & 70\% & 75\% & 65\% & 70\% & 80\% & 100\%
\end{pmatrix}$$

Tutorial exercise 2

Enhanced ESG score & tracking error control

Question 1

Calculate the ESG score of the benchmark.

Tutorial exercise 2

Enhanced ESG score & tracking error control

- We note b_i and $\mathcal{S}_i$ the weight in the benchmark and the ESG score of Stock i
- The ESG score of the benchmark is equal to:

$$\mathcal{S}(b) = \sum_{i=1}^{8} b_i \cdot \mathcal{S}_i = 0.1690$$

Tutorial exercise 2

Enhanced ESG score & tracking error control

Question 2

We consider the EW and ERC portfolios. Calculate the ESG score of these two portfolios. Define the ESG excess score with respect to the benchmark. Comment on these results.

Tutorial exercise 2

Enhanced ESG score & tracking error control

- The composition of the EW portfolio is $x_i = 12.5\%$ and we have:

$$\mathcal{S}\left(x_{\mathrm{ew}}\right) = \sum_{i=1}^{8} \frac{\mathcal{S}_i}{8} = -0.1125$$

- The composition of the ERC portfolio is $x_1 = 12.42\%$, $x_2 = 14.03\%$, $x_3 = 10.17\%$, $x_4 = 13.79\%$, $x_5 = 7.59\%$, $x_6 = 12.34\%$, $x_7 = 20.61\%$ and $x_8 = 9.06\%$. We have:

$$\mathcal{S}\left(x_{\mathrm{erc}}\right) = \sum_{i=1}^{8} x_i \cdot \mathcal{S}_i = 0.1259$$

Tutorial exercise 2

Enhanced ESG score & tracking error control

- The ESG excess score with respect to the benchmark is:

$$\mathcal{S}(x \mid b) = \mathcal{S}(x) - \mathcal{S}(b)$$

We have:

$$\begin{aligned}\mathcal{S}(x_{\mathrm{ew}} \mid b) &= -0.1125 - 0.1690 = -0.2815 \\ \mathcal{S}(x_{\mathrm{erc}} \mid b) &= 0.1259 - 0.1690 = -0.0431\end{aligned}$$

- The two portfolios are riskier than the benchmark portfolio in terms of ESG risk

Tutorial exercise 2

Enhanced ESG score & tracking error control

Question 3

Write the γ-problem of the ESG optimized portfolio when the goal is to improve the ESG score of the benchmark and control at the same time the tracking error volatility. Give the QP objective function.

Tutorial exercise 2

Enhanced ESG score & tracking error control

- We have:

$$
\begin{array}{rcl}
x^{\star} & = & \arg\min \frac{1}{2}\sigma^{2}\left(x \mid b\right) - \gamma \mathcal{S}\left(x \mid b\right) \\
 & \text{u.c.} & \left\{ \begin{array}{l} \mathbf{1}_n^{\top} x = 1 \\ \mathbf{0}_n \leq x \leq \mathbf{1}_n \\ x \in \Omega \end{array} \right.
\end{array}
$$

- Since $\sigma^{2}\left(x \mid b\right) = \left(x - b\right)^{\top} \Sigma \left(x - b\right)$ and $\mathcal{S}\left(x \mid b\right) = \left(x - b\right)^{\top} \mathcal{S}$, we deduce that the QP objective function is:

$$
x^{\star} = \arg\min \frac{1}{2} x^{\top} \Sigma x - x^{\top}\left(\gamma \mathcal{S} + \Sigma b\right)
$$

Tutorial exercise 2

Enhanced ESG score & tracking error control

Question 4

Draw the efficient frontier between the tracking error volatility and the ESG excess score[a].

[a] We notice that $\gamma \in [0, 1.2\%]$ is sufficient for drawing the efficient frontier.

Tutorial exercise 2

Enhanced ESG score & tracking error control

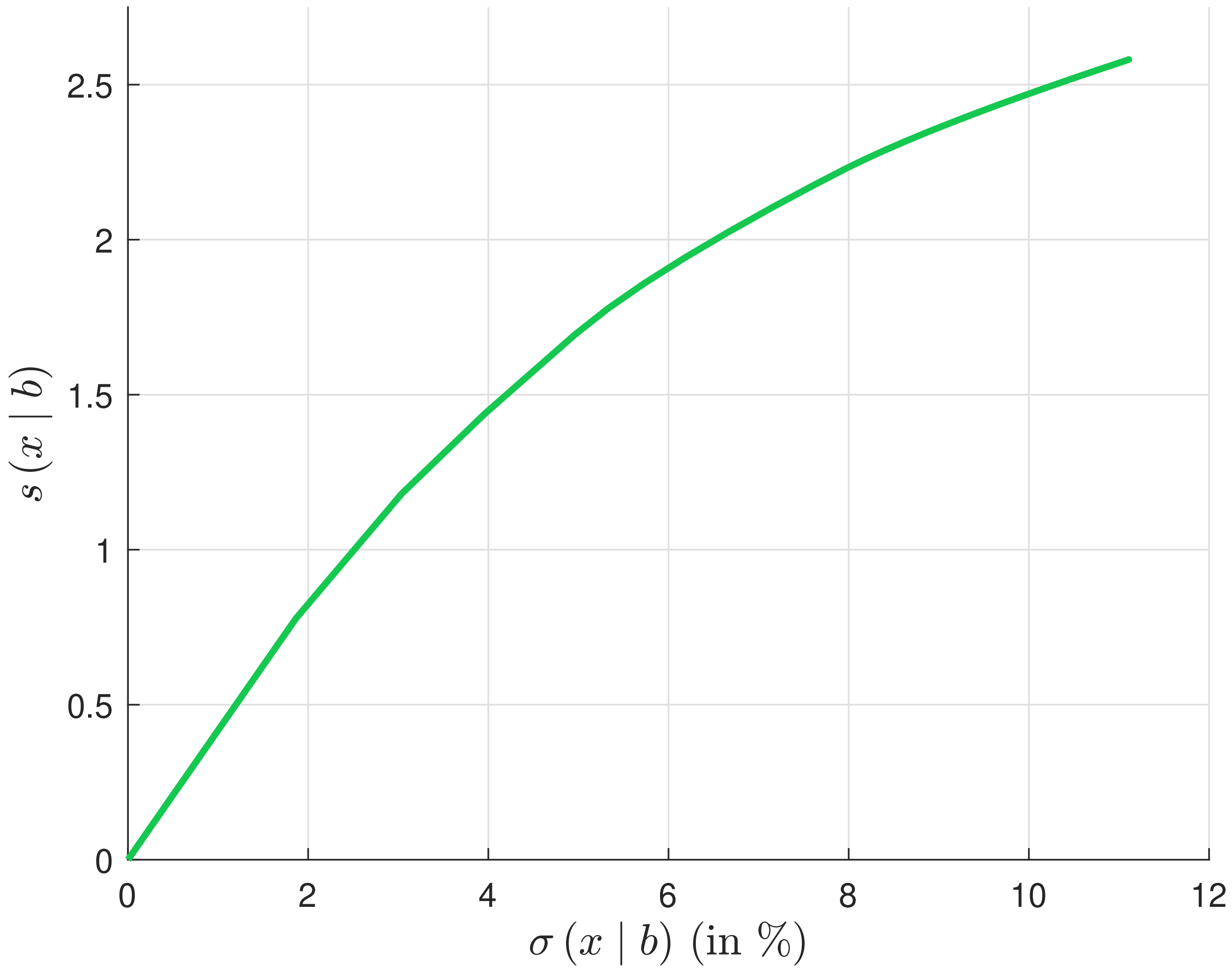


Figure 91: ESG efficient frontier

Tutorial exercise 2

Enhanced ESG score & tracking error control

Question 5

Using the bisection algorithm, find the optimal portfolio if we would like to improve the ESG score of the benchmark by 0.5. Give the optimal value of γ. Compute the tracking error volatility $\sigma(x \mid b)$.

Tutorial exercise 2

Enhanced ESG score & tracking error control

- The solution is equal to:

Stock	s_i	b_i	$x_i^\star$
#1	-1.200	23.000	25.029
#2	0.800	19.000	14.251
#3	2.750	17.000	21.947
#4	1.600	13.000	27.305
#5	-2.750	9.000	3.718
#6	-1.300	8.000	1.339
#7	0.900	6.000	1.675
#8	-1.700	5.000	4.736

- The optimal value of γ is 0.02768%
- The tracking error volatility is equal to 1.17636%

Tutorial exercise 2

Enhanced ESG score & tracking error control

Question 6

Same question if we would like to improve the ESG score of the benchmark by 1.0.

Tutorial exercise 2

Enhanced ESG score & tracking error control

- The solution is equal to:

Stock	s_i	b_i	$x_i^\star$
#1	-1.200	23.000	21.699
#2	0.800	19.000	12.443
#3	2.750	17.000	28.739
#4	1.600	13.000	33.555
#5	-2.750	9.000	0.002
#6	-1.300	8.000	0.000
#7	0.900	6.000	2.433
#8	-1.700	5.000	1.129

- The optimal value of γ is 0.07276%
- The tracking error volatility is equal to 2.48574%

Tutorial exercise 2

Enhanced ESG score & tracking error control

Question 7

We impose that the portfolio weights can not be greater than 30%. Find the optimal portfolio if we would like to improve the ESG score of the benchmark by 1.0.

Tutorial exercise 2

Enhanced ESG score & tracking error control

- The solution is equal to:

Stock	s_i	b_i	$x_i^\star$
#1	-1.200	23.000	20.116
#2	0.800	19.000	14.082
#3	2.750	17.000	29.481
#4	1.600	13.000	30.000
#5	-2.750	9.000	0.644
#6	-1.300	8.000	0.000
#7	0.900	6.000	4.662
#8	-1.700	5.000	1.015

- The optimal value of γ is 0.07355%
- The tracking error volatility is equal to 2.50317%

Tutorial exercise 2

Enhanced ESG score & tracking error control

Question 8

Comment on these results.

Tutorial exercise 2

Enhanced ESG score & tracking error control

- We notice that the evolution of the weights is not necessarily monotonous with respect to the ESG excess score $\mathcal{S}(x \mid b)$. For instance, if we target an improvement of 0.5, the weight of Stock #1 increases (23% $\Rightarrow$ 25.029%). If we target an improvement of 1.0, the the weight of Stock #1 decreases (25.029% $\Rightarrow$ 21.699%)
- Generally, the optimiser reduces the weight of stocks with low ESG scores and increases the weight of stocks with high ESG scores
- Nevertheless, the weight differences are not ranked in the same order than the ESG scores. For instance, if we target an improvement of 0.5, the largest variation is observed for Stock #4, which has an ESG score of 1.6. This is not the largest ESG score, since Stock #3 has an ESG score of 2.75
- This is due to the structure of the covariance matrix (Stock #3 is riskier than Stock #4)