Life Stress
Social Risk and Nature Risk
Methodology Report
January 2025

About 1in1000

1in1000 is research collaboration between Oxford Sustainable Finance Initiative and Theia Finance Labs (Formerly 2° Investing Initiative Germany) that brings together new & existing research projects on long-termism, climate change, and (inter-)connected future risks for financial markets, the economy, and society. Its objective is to develop evidence, design tools, and build capacity to help financial institutions and supervisors to mitigate and adapt to future risks and challenges. The programme focuses on climate change (inter-) connected risks and challenges, notably risks stemming from ecosystem services, as well as risks from social cohesion and resilience.

About Theia Finance Labs

Theia Finance Labs (formerly 2° Investing Initiative Germany) is an independent, non-profit think tank incubating research solutions for the financial sector that help solve the climate crisis. The Theia Finance Labs name is inspired by the Greek goddess of sight, the light of the blue sky, and the value of gold, Theia, and by the Greek word Aletheia, which means "disclosure" or "truth", literally "the state of not being hidden". The new brand thus mirrors our goal to develop evidencebased research and tools that shed light on the intersection of finance, climate change, and longterm risks. Theia operates as a 100% non-profit organization

FUNDING: The report forms part of the LIFE STRESS project. The LIFE STRESS project has received funding from the LIFE Programme of the European Union.' The contents of this publication are the sole responsibility of Theia Finance Labs and do not necessarily reflect the opinion of the European Union.

TABLE OF CONTENTS

TABLE OF FIGURES

TABLE OF TABLES

Introduction

Climate change poses significant challenges to the financial system. Well-known risk channels, such as transition risk and physical risk, have become central considerations in economic planning and decision-making. Transition risk focuses on the strategic challenges corporations and governments face in planning for a low-carbon transition, while physical risk examines damages to assets like buildings and infrastructure caused by climate hazards. However, these dimensions alone do not capture the full breadth of risks associated with climate change. Crucially, two additional dimensions of risk remain still underrepsented in practice.

1. **Social Risk:** The social consequences arising from climate change, or the measures taken to mitigate and adapt to it
2. **Nature Risk:** The risks to and from natural ecosystems, biodiversity, and the ecosystem services upon which economies and communities depend

Previous research has already shown the material importance of these channels. For example, Otto et al. (2017) analyzed impacts on health, safety, food security, and displacement, showing that climate change disproportionately affects certain demographic groups. They also explored intergenerational climate justice, noting that early-life social impacts can limit future opportunities. Similarly, Carleton & Hsiang (2016) studied how physical climate events influence social factors, such as regional conflicts. Research by Arabadjieva & Bogojević (2024) examined the European Green Deal's phase-out of coal and mining activities, also highlighting how these policies create conflicts and pointing out that the EU's current just transition measures are too narrow to provide effective solutions. International institutions like the United Nations and the World Bank have underscored the broader social implications of climate change, including poverty, livelihood disruptions, and threats to human security (World Bank, 2023) (United Nations, 2024). Similar**,** Studies like Babibulah et al. (2022) find how climate variables such as temperature, precipitation, and natural disasters drive biodiversity loss (Habibullah, 2022) . Weiskopf, et al. (2020) document changes in species behavior, productivity, and interactions based on climate chance and shows how these shifts affect the benefits ecosystems provide to our society. Prominent figures in central banking, like the deputy govenor of the Bank of England, Sarah Breeden, have also already ackkowledged the potential materiality of nature risk and the resulting decline of ecosystem services on the financial system (Breeden, 2022), which Is further supported by reports for example by the Green Finance Institute (2024) which give an indication of the effect on GDP nature risk events can take.

While research on social and nature risks is growing, and leading institutions are starting to recognize them, they remain insufficiently integrated into risk assessment practices and methodologies. This report addresses this gap. In part 1, we introduce a methodology using a steel-based risk model combined with open-source employment data to estimate the workforce impacts of a low-carbon transition. In part 2, we explore methods to assess the financial risks associated with ecosystem service loss. These tools aim to help institutions understand their exposure to these broader risks and demonstrate their importance to individual firms, the financial system, and the wider economy.

Part 1: Social Risk

Introduction: Social Risks

Social risk, in the context of climate change, refers to the potential societal impacts that can arise from both the direct effects of climate change and the actions taken to address it. These risks often manifest as job losses, displacements, or rising inequality, particularly in vulnerable communities and sectors heavily reliant on carbon-intensive activities. Addressing social risk requires an awarness of how climate policies interact with social and economic systems to ensure that the benefits of the low-carbon transition are equitably distributed and minimizing adverse effects on the affected parts of the population. Without a good understanding of social risk, a just transition that includes and supports different type of workers and communicities cannot be guaranteed.

Social risk is closely connected to transition risk, which focuses on the financial and operational stress businesses and economies face during the shift to a low-carbon economy. While transition risks often emphasize market disruptions, stranded assets, or regulatory compliance costs, social risks underscore the broader societal consequences of these changes. The two types of risks are deeply interdependent. Efforts to reduce transition risks, such as regulatory mandates to phase out emissions, can inadvertently amplify social risks if they lead to widespread job losses, intensify economic disparities, or leave communities without adequate support. Conversely, prioritizing short-term social stability by delaying or weakening climate action can escalate long-term transition risks, resulting in increased economic costs, environmental degradation, and social upheaval.

One key dimension of social risk is the loss of employment, which can occur as industries adapt to stricter environmental regulations, existing technologies reach the end of their usability, and economies transition to low-carbon processes. This challenge is particularly grave in sectors such as energy, manufacturing, and transportation, which are highly exposed to political decarbonization pressures. Without proactive planning, these transitional changes can excessibley affect workers in these high emission sectors or concentrated roles, which further effects the dependent local economies and social cohesion. In this report, we focus on how social risks, specifically employment impacts, are linked to the transition to a greener economy.

Social Risk in the Steel Sector: A Model for Transition Risks

We have incorporated social risk into our existing transition risk model (TRISK) by adding a dedicated dimension to analyze these impacts. This addition focuses on the specifically for social risk newly implemented steel sector into our risk analysis portfolio. The steel sector is a critical industry with significant implications for employment. Nevertheless, the social risk methodology we developed can be applied also to other sectors, i.e. power, oil and gas extraction and coal mining. Steel serves as an ideal case study because it is both foundational to industrial development and has potential high vulnerability to climate change transition efforts, with it it being the largest carbon-emitting manufacturing sector (World Economic Forum, 2023), being responsible for 7% of all global man made GHG emissions.

Already today, the steel sector is experiencing social risk impacts. For instance, Thyssenkrupp Steel's recently announcted to cut 5,000 jobs by 2030, which highlights the tangible consequences of restructuring in response to economic and environmental pressures (Reuters, 2024). As the industry adapts to the concept of decarbonization, job losses like these are likely to become more frequent.

Our approach uses data from the Global Energy Monitor (GEM) that enables us to quantify and assess the social risks associated within this sector on individual plant level[1]. By integrating social risk analysis into our model, we aim to advance our existing framework and help improve the understanding of the challenges of climate change and climate transitions. This newly added social risk dimensions provides new insights for our users and emphasizes the urgent need to consider social dimensions in climate policy and corporate decision-making.

In the following section we will introduce the methodology, the relevant data sources and wrangling assumptions, show the results of the social risk analysis in the steel sector and discuss potential limitations of our approach. After that, we also highlight an alternate methodology approach, which addresses these limitations and presents a potential update in the methodology for future work.

Methodology V1: Social Risk and Steel in the TRISK methodology framework

Our methodology for assessing social risk in the steel sector is built into the broader TRISK framework and is carried out in two key stages.

Stage 1: Integrating Steel into the TRISK Framework

In the first stage, we integrate steel as a sector within the existing TRISK model framework. This involves applying the same transition risk logic that underlines the overall model.

The process begins with asset-level five-year production forecasts, which provide a detailed view of the strategic positioning of specific assets and their producion processes and capacity. Plant specific productions are extrapolated into two distinct scenarios:

- **Baseline Pathway:** This reflects a "business as usual" trajectory, where no additional climate policies or interventions are implemented beyond those already in place. It projects production levels to 2050 based on current trends.
- **Target Pathway:** This scenario assumes a transition to meet specific climate goals, such as limiting global warming to 1.5°C or achieving Net Zero by 2050.

After that, we model the shock scenario. Under this scenario, production follows the baseline pathway until a designated "shock year," when new climate policies are assumed to be implemented. This introduces an abrupt alignment to the target pathway. During this adjustment, production levels are recalibrated to meet the target trajectory, while also compensating for prior misalignment to maintain the overall carbon budget.

[1] GEM data can be freely accessed here: https://globalenergymonitor.org/

To quantify financial impacts, we translate production capacities into net production values using capacity factors. Net production is then converted into revenue estimates using unit prices, which are further translated into profit projections using net profit margins obtained from third party financial data providers. The result is the calculation of the Net Present Value (NPV) for each company under both baseline and shock conditions. This allows us to assess how a company's value changes depending on its production profile during the transition. An optional carbon tax mechanism can be incorporated to account for the costs associated with total emissions that are generated through the prouction processes. Figure 1 below highlights the main model mechanics of the Transition Risk model

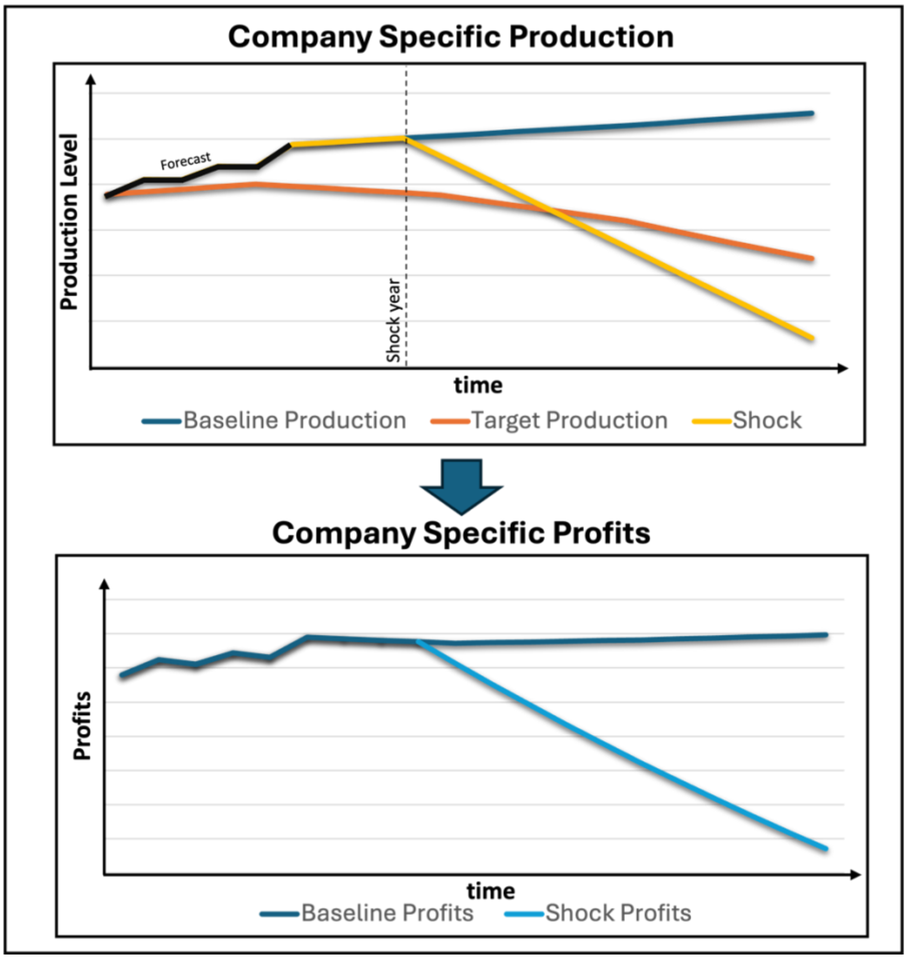

Figure 1 TRISK Mechanism

Stage 2: Social Risk Analysis

The second stage focuses on translating transition risk model outputs into social risk outputs. Using the financial projections from Stage 1, we determine whether and when a company is likely to become unprofitable during the transition period.

If a company's profits reach zero, it is assumed that the business can no longer operate, leading to plant closures and job losses for employees at the affected sites. These shutdowns are used to estimate the scale and timing of potential unemployment in the sector.

Conversely, we also consider the **positive social risk effects** associated with the transition. For example, new plants using green technologies may be established, creating new employment opportunities. These job gains are factored into the analysis to provide a balanced view of social risk outcomes during the transition.
Figure 2 shows the profit development of an exlamporatory company. Once the profits of the company in the shock scenario reaches 0, the company workforce is immediately laid off.

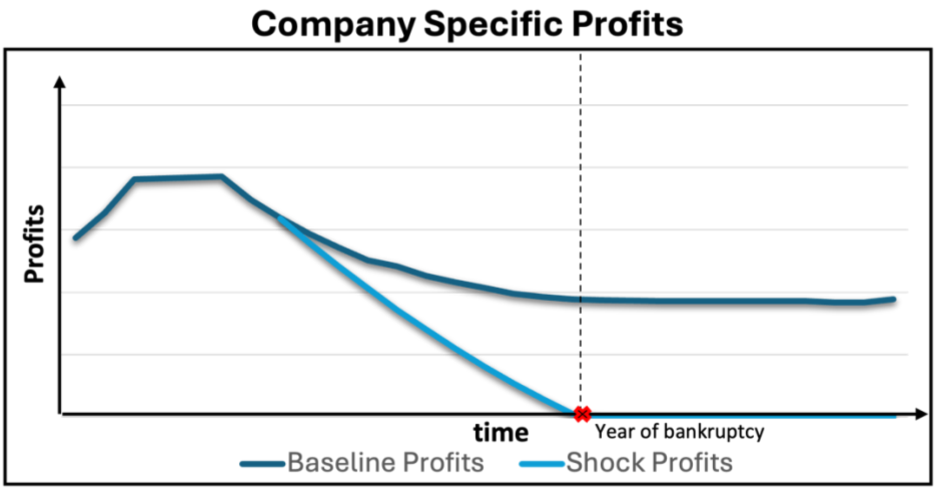

Figure 2 Illustration of company profits and the year of bankruptcy

Using the just mentioned approach has several benefits. First of all, this mirrors the already existing TRISK model methodology. TRISK is a recognized and tested model, which has been performed by several financial institutions. Following the model logic of TRISK gives the advantage of several years of feedback and improvement cycles. One disadvantage of mirroring the approach using steel might be that It underestimates the political significance of having steel plants in a country. This and further limitations are highlighted in the limitations section below.

Data Inputs

While the main model narrative follows TRISK, there are still several difference on how the steel sector is hanlded in relation to other scetors. These differences are mostly rooted in data availability and quality. The next section covers the different data inputs needed to run the designed social risks exercise, with specific acknowledgement also to running it with a steel sectoral focus.

Asset Data

For the underlying asset data of the steel plant, we are using data provided by GEM.
This is a first deviation of the main TRISK model. In the main model, we are using asset level data provided by Asset Impact. Asset Impact also provides data for the steel sector, which we analysed within the concept of running Social Risk, but decided to switch to GEM for the asset level data estimates.

The reasoning for this are as follows:

- First of all, both datasets give current steel capacity for different production processes. However, the GEM dataset also gives extremly valuable different data variables, such as the exact location of the steel plant, measured in longitude and latitude, the furnaces used by each steel plant, the plant age, assigned workforce size and also when a future plant or extension is announced to start, and when other parts of a plant are planned to retire. All this data is not available in this detail from Asset Impact.
- Asset Impacts main value comes from its data on forecasting production capacity for the next 5 years. This is not explcictely given by GEM. However, the Asset Impact forecast in the steel sector has certain characteristics which make the analysis with it not as valuable as with the power, coal or oil and gas sector. While GEM does not explcitely gives a forecast, it can be constructed using plant specific announcements of retirements and build outs.
- GEM data is also open source, which makes sharing the underlying data and entire model assumptions with our counterparties simple and facilitates the understanding of the model.

The GEM dataset provides detailed information about steel plants worldwide, with key variables including plant identification (Plant ID), ownership (Owner and Owner PermID), and location (Coordinates). It highlights production capacities, focusing on crude steel capacity (Nominal crude steel capacity (ttpa)), seperated into Blast Oxygen Furnace (BOF), Electric Arc Furnace (EAF) and Open Hearth Furnace (OHF), and crude iron capacity (Nominal iron capacity (ttpa)), seperated into Direct Reduced Iron (DRI) and Blast Furnace (BF), which are key for understanding the scale of operations for each plant and the underlying production process. The dataset also includes operational timelines, with Start date and Closed/idled date indicating the phase in and phase out of specific plants. These phase in or retirements can be sources to a singular plant, where the entire facility is either constructed or closed, but more often it refers to a partial build out or retirement of an existing "main plant" in the dataset. Additionally, Workforce size shows the employment at each facility.

GEM Wrangling

The wrangling process involved a series of transformations and decisions to convert the initial GEM dataset into a consistent, time-series dataset suitable for our model framework. First, we focus only on data points relevant to our target analysis, this being steel capacities, plant identifiers, plant statuses, and important future dates.

The data is also filtered so that only plants with meaningful forward-looking potential remained. Assets with a canceled, mothballed, or retired states with no future are excluded, while announced or construction-stage plants without a known start date are also removed. For plant retirement data, only retired plants scheduled to close after 2023 are kept. Non-numeric or unknown closing dates are set to NA, and all capacity fields are standardized into tonnes per annum.

A critical part of the wrangling is cleaning the steel making process columns. We convert unknown or N/A values into zero to ensure that further wrangling can be performed. Because the GEM dataset combined multiple iron- and steelmaking routes and given the importance of these different prodution routes based on their carbon impact, it is important to reassign capacities to the correct technology categories. The GEM data only gives capacity for the steel making process (BOF, EAF, OHF) and in a separate column the iron making processes (BF, DRI). We used several assumption to align these data for each individual plant.

1. A plant would always use first its own iron to generate steel. For example, if a plant produces steel using BOF and iron using BF, the steel making capacity is allocated towards the BF-BOF production route. This route was asigned then even when the total iron and steel production did not match completely.
2. If a plant produces steel using one specific technology, but iron using two processes, the steel capacity is seperated into the different technology routes by the ratio of the DRI vs BF iron production. So a plant using BOF steel capacity would be seperated into DRI-BOF and BF-BOF, based on the calculated ratio of DRI and BOF towards total iron production.
3. If no iron production is known, we just categorize the steel productio as EAF, OHF or BOF.
4. If the plant has two different steel making routes, and only one iron making process, the relted steel capacity values are directly linked to the relevant iron process. So for example, a plant operation on BOF and EAF using DRI, the capacity will be seperated 1to1 to DRI-BOF and DRI-EAF
5. If a plant has both BF and DRI iron production processes available, and at the same time both BOF and EAF steel capacity are present, our approach ultimately assigns all BOF steel capacity to BF-BOF and all EAF steel capacity to DRI-EAF.

Figure 3 shows a simplified example on how the wrangling process transforms the different steel and iron routes. The final result is a set of technology-specific capacity columns that reflect the relevant production process.

Raw GEM Data

	Steel Making Route		Iron Making Route	
Case #	**BOF**	**EAF**	**BF**	**DRI**
1	100		100	
2	500		250	250
3	100	200		
4	100	100	200	
5	100	100	100	100

Wrangling Process

Final Data

	1in1000 Model Technology					
Case #	BOF	**EAF**	**BF-BOF**	**BF-EAF**	**DRI-BOF**	**DRI-EAF**
1			100			
2			250		250	
3	100	200				
4			100	100		
5			100			100

Figure 3 Wrangling Example, values in tpa

A similar challenge arises with workforce data. Some plants lack workforce size figures and just show unknown or N/A. We address this by building a regression model from plants where reliable workforce data is given, then using that model to estimate missing workforce sizes for other plants, particularly those in construction, announced, or operating states. The regression model works based on the amount of capacity available in each of the different production routes (BF-BOF, DRI-BOF, BF-EAF, DRI-EAF, BOF, EAF)[2]. The coefficients calculated can be seen in table 1 below.[3]

Term	Coefficient	tvalue	Signficance
Intercept	1092	5.189	Highly significant
BF-BOF	0.00089	19.8	Highly significant
BF-EAF	0.00061	1.869	Marginally significant
DRI-EAF	0.00083	4.824	Highly significant
DRI-BOF	-0.00033	-0.308	Not significant
BOF	0.00103	6.483	Highly significant
EAF	0.00006	0.346	Not significant

Table 1 Workforce Regression

For retired plants without workforce data, the workforce is allocated proportionally based on the capacity the reitred plant represented relative to the main asset's total capacity. This ensures that the reduction in capacity due to retirement was matched by a corresponding reduction in workforce based on the original plant workforce size.

Once the dataset is cleansed, filtered, and capacities are consistently allocated, it is reshaped into a "long" format, creating annual time-series data for each asset, technology, and year.

The next wrangling step is creating the forecast. For this, we use the operating status, start date and end date. If a plant is announced or planned, it is assigned a start date at some point after 2023, as indicated by the raw data. On the other hand if it is retired, then it shows an end date, which highlights the year after 2023 the plant is about to close. The forecast is created by matching these plant capacity announcement and retirements onto a time series. An announced EAF plant would have 0 capacity until the designated start date, on the other hand a retired plant would reduce their capacity to 0, after the closing date.
By aggregating the dataset then on plant_level, we ensure that that expansions, retirements, and technology changes over time can be traced. A plant in the newly created dataset thus can have varying capacity in the forecasted period, based on these changes.

[2] Note there is one more production route in BF-OHF, but only two plants were in the GEM dataset and both had complete data
[3] Some of the coefficients were not significant. We expect this to be mostly caused by a smaller sample size within the GEM dataset. We address this issue again in the limitation section.

We also separate the final production and workforce size based on company ownership. Most of the plants are owned by one parent company, however some have multiple assigned owners. In that case, the steel producing capacity, as well as the workforce are split to allocate the designated share according to a companies total ownership of the steel plant.

Finally, the current TRISK model framework uses a 5 year production forecast. In order to be aligned with the other sectors, we cut off the forecast timeseries after 2028.

Capacity Factors and Emission Factors

Technology specific capacity factors are necessary to transform the steel capacity into net production outputs. GEM actually offers some historic production values for some plants, which could be used to calculate implied capacity factors, however our analysis showed that these implied factors were met with several computational inconsistencies, i.e. that a calculated capacity factor are above 1, which indicate a higher net production than the plant has the capacity to produce. We thus refer here to a seperate dataset “climate trace”. The climate trace database shows capacity factors for several different steel plants over time. We calculat historic average capacity factors that are country specific and match those to our existing asset database from GEM. One issue with this however is that the technology process granularity of Climate Trace is not very high. Climate Trace only gives data seperated into BF-BOF and EAF technology trees. We decide to still use this data and duplicate the values for different technologies. The capacity factors for BF-BOF are used for BOF, DRI-BOF and BF-OHF, while the ones for EAF are used for EAF, BF-EAF and DRI-EAF.

Emission factors are also required, if the analysis should include a carbon tax dimension. Similarily to capacity factors, we use data from climate trace on country level emission factors, which however have the same technological granularity limitations.

Scenario Data

For steel scenarios, we use data provided by the Mission Possible Partnership (MP). The MP is a coalition of organizations helping the world’s toughest-to-abate industries reach net-zero emissions by 2050 (Mission Possible , 2022). It unites business, finance, and policy leaders to produce practical roadmaps, align market incentives, and guide stakeholders toward concrete actions that make cleaner, more sustainable production methods possible. The steel scenarios provide pathways to understand how the steel sector might evolve and decarbonize under different conditions. There are two main scenarios relevant for our work: a baseline scenario that assumes no specific coordinated policies or incentives and a carbon cost scenario that includes a global carbon price and represents the target trajectory for achieving net-zero emissions.

Technology Trajectories

In the baseline scenario, the steel industry continues much as it does today, with new low-CO_2 methods only appearing where they already make economic sense. There is no strong push or structured policy driving change. By contrast, the carbon cost scenario assumes coordinated action and an implemented carbon price. This encourages the industry to adopt technologies with the lowest total cost of ownership when both direct and indirect emissions face a price. Because this scenario is consistent with a net-zero and 1.5°C climate target, it serves as a key reference for forward planning.

Although the MP scenarios are helpful, some data is missing or incomplete. Certain technologies do not have full time-series coverage from 2020 to 2050, and some have no data in the baseline or the carbon cost scenario. For these technologies, we use specific assumptions to fill in the data using either intrapolations or insteade fill in those missing years with the earliest available data point. For other technologies data is missing in the final years of the carbon cost scenario, and it seems reasonable to assume that its output goes down to zero as a result of decarbonization policies. MP provides multiple different technology trees for steel, but only on a global level. Figure 4 below shows the trajectories of the different steel technologies offered by MP.[4]

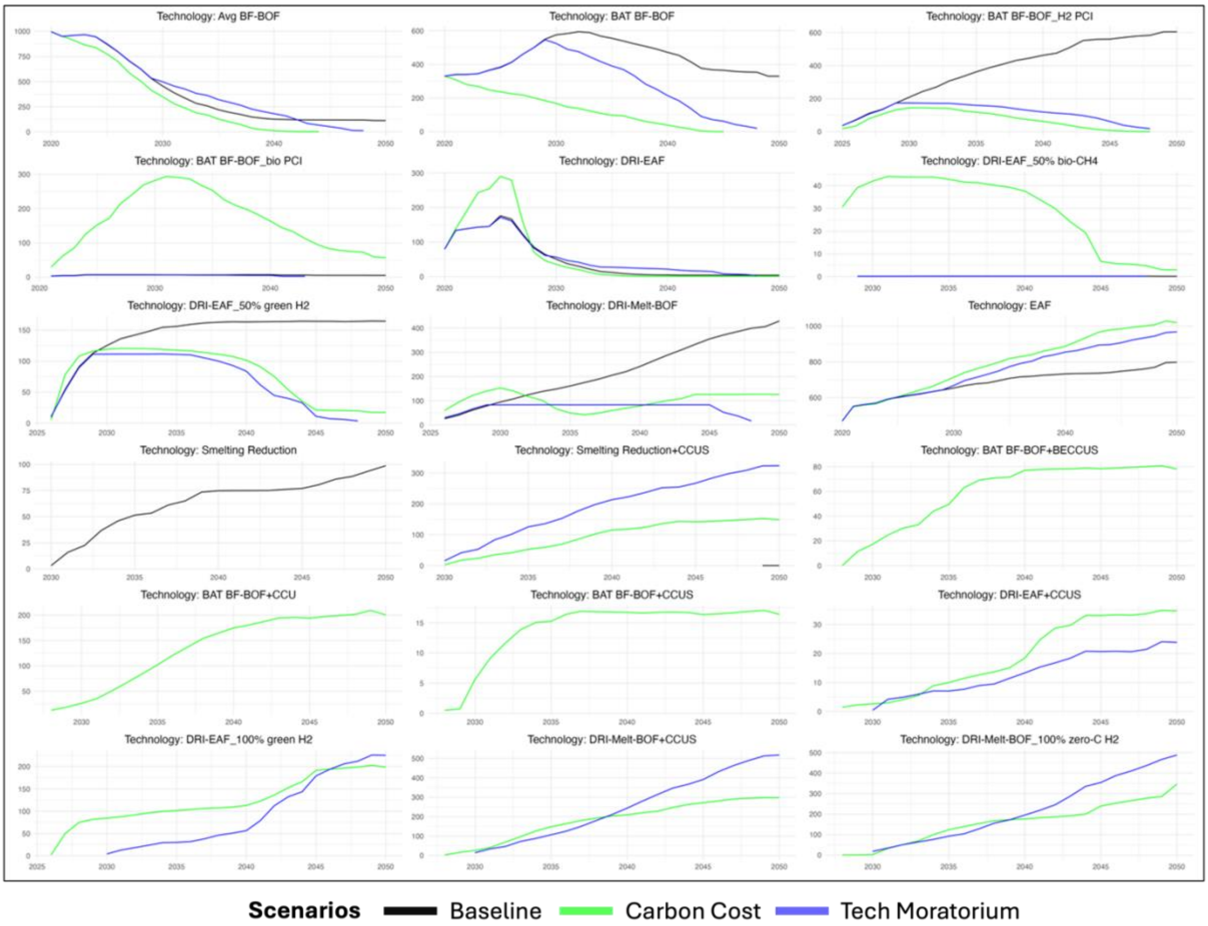

Figure 4 Technology Scenario Trajectories by MP

Steel price

There is no available data on the progression of steel prices in these two scenarios. However, MP offers levelized costs (LC) data for these scenarios by region. Because there is no global number, we take an average across regions to create a global estimate. We then use the formula shown below, to estimate a steel price proxy per technology. The

[4] Note that figure 4 also shows the values for a third scenario called “Techn Moratorium”. This scenario made available by MP is however not included in our steel model.

intuition behind the formulas shown below is that an implied price can be calculated based on the deduction and break up of Net Profit Margin (NPM) equations.
The NPM this case is estimates based on available financial data on sector level. We also apply a cost factor. The cost factor is calculated every year and is aimed to be applied to the implied price of (5). It is designed to capture the inverse trend of growth or decline in the LC data. The intuition behind this is that if a technology would have rising costs, the implied price with formula (5) will keep a constant NPM. This in turn would indicate that steel companies could just push rising costs of steel generation on to consumers indefinitely, which is not realistic. In contrast, we want to cover that rising costs will ultimately eat away the NPMs of companies, as they are unable to just pass on the cost increases. This approach is also applied for prices in the power sector in the TRISK model.

$$(1)\quad NPM = \frac{Profit}{Revenue}$$

$$(2)\quad NPM = \frac{Production\ (price - LC)}{Production * price}$$

$$(3)\quad NPM = \frac{(price - LC)}{price}$$

$$(4)\quad LCOE = (1 - NPM) * price$$

$$(5)\quad implied\ price = \frac{LC}{(1 - NPM)}$$

$$(6)\quad cost\ factor_t = \frac{LC_{t0=2020}}{LC_t}$$

$$(7)\quad final\ price_t = implied\ price * \ cost\ factor_t$$

Financial Data

The final missing piece is final data that is matched to the company owners of the steel assets. We use data from Refinitif Eikon on NPMs, leverage ratios, volatilities and pds. A lot of the steel parent companies are not publicly owned, hence we are using country level averages for the available financial data we have from the steel sector.

Social Risk Results

From the GEM data and using regression analysis, we have available steel plants and corresponding workforce data for 81 different countries.

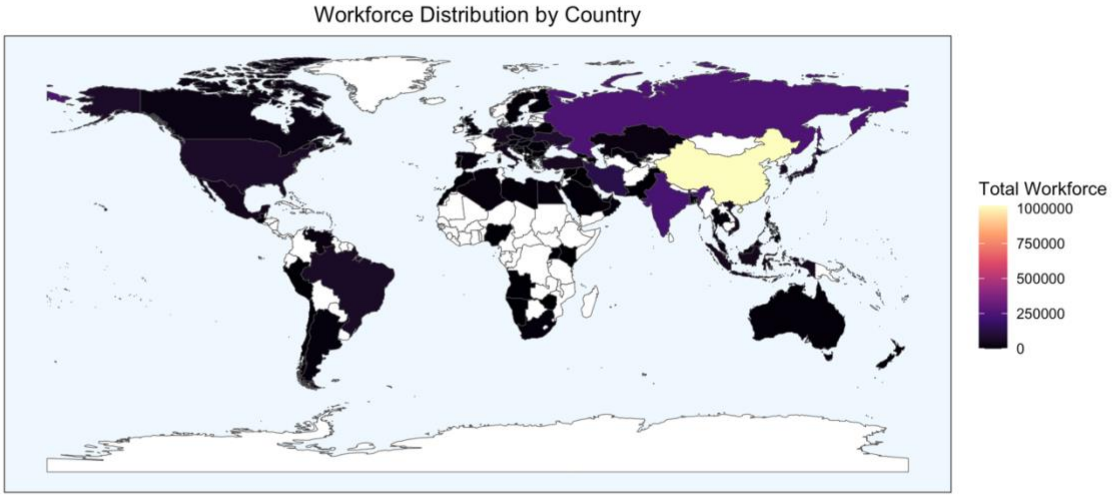

Figure 5 Steel workforce by country

Figure 5 shows which countries are covered in the database and also the corresponding total workforce size by all the steel plants in the relevant country in 2023. By far the largest workforce size is located in China, with around 1.000.000 people employed in 2023 in the steel sector. This is backed by the dominant market position of china in the steel market. Followed by China, Russia and India have the second and thrid largest cumulative workforce with around 244.000 and 231.000 respectively. In total, the global steeplants sum to a workforce size of 2,673,092.

In the model, we can use multiple different settings to estimate the social risk effect. For now, we are using a default model run with a shock year in 2030 without the implementation of the carbon tax. We highlight the implications of adding a carbon tax to the model paramters later in this report.

Figure 6 below illustrates the geographic distribution of steel plants across countries, along with the number of jobs affected by layoffs. Most GEM steel plants are concentrated in Eastern China and Japan, Central Europe, Russia, and India, with a smaller number located in the Americas, Africa, and Australia. The size and darkness of the circles in the diagram indicate the scale of layoffs, with larger and darker circles representing more significant job losses due to the transitional shock.
Notable trends include the significant layoffs observed in many steel plants in Russia, as well as in selected plants in India and China. An isolated plant in Venezuela also shows a high number of job losses. In absolute terms, the highest losses are recorded in China, India, and Russia, with 829,000, 195,000, and 114,000 jobs lost, respectively.
What stands out is the global nature of the impact. Every populated continent is affected, albeit to varying degrees. In total, 1,795,060 jobs are affected, more than two-thirds of the currently implemented steel sector workforce.

Figure 6 Plant location and laid off workforce

In addition to analyzing the absolute social risks associated with transitional shocks, we can also examine the percentage of workforce layoffs by 2050 compared to the current workforce in existing steel plants. This provides further insights into the relative impact across countries.

Ten countries are projected to lose their entire steel sector workforce, highlighted in black in figure 7. These countries include the United Arab Emirates, Austria, Bahrain, Kenya, Libya, Nigeria, the Netherlands, Qatar, Slovakia, and Venezuela. Together, these complete workforce losses account for over 65,000 jobs.

Another notable observation is the difference in relative impacts despite high absolute losses in China, India, and Russia. Russia's more diversified steel production portfolio makes it significantly less affected in relative terms compared to China and India.

Specific examples of larger relative impacts include Germany, where 87% of the steel workforce is laid off, affecting 46,600 people, Ukraine, with 92% of the workforce laid off, equating to 76,000 jobs lost, and Vietnam, with 87% of its workforce laid off, representing 38,000 jobs.

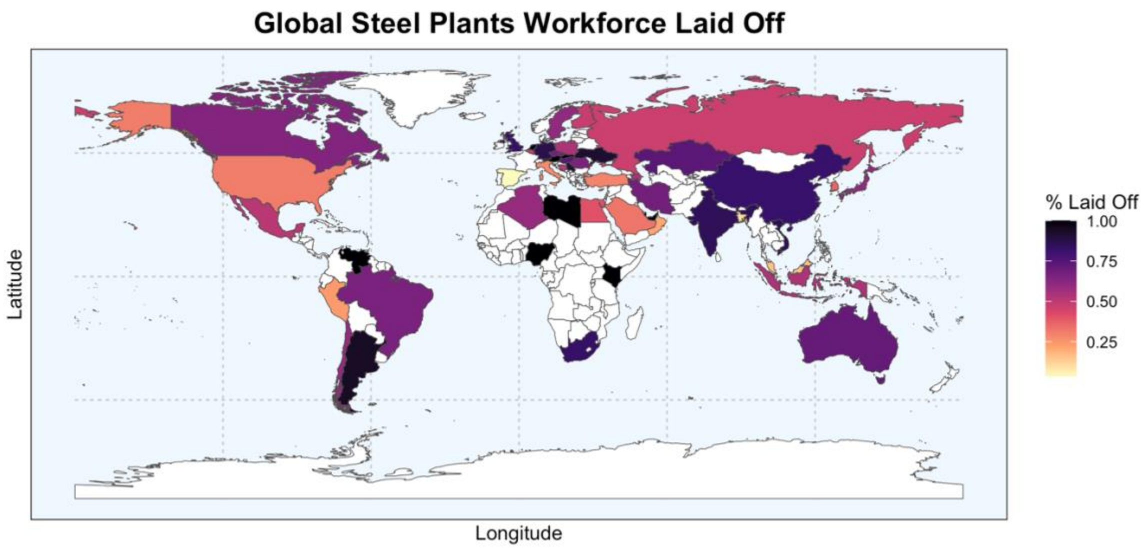

Figure 7 Layoff Ratio per country

Figure 8 highlights the distributionof the ratios of workforce layoffs across countries, with a mean loss of 63% per country. Despite this rather significant average, some countries have managed to contain their losses more effectively. For example, the United States, ranked 7th in total steel employment, limits workforce losses to 31%. Spain experiences the least negative impact, with only 3% of its current steel workforce affected.

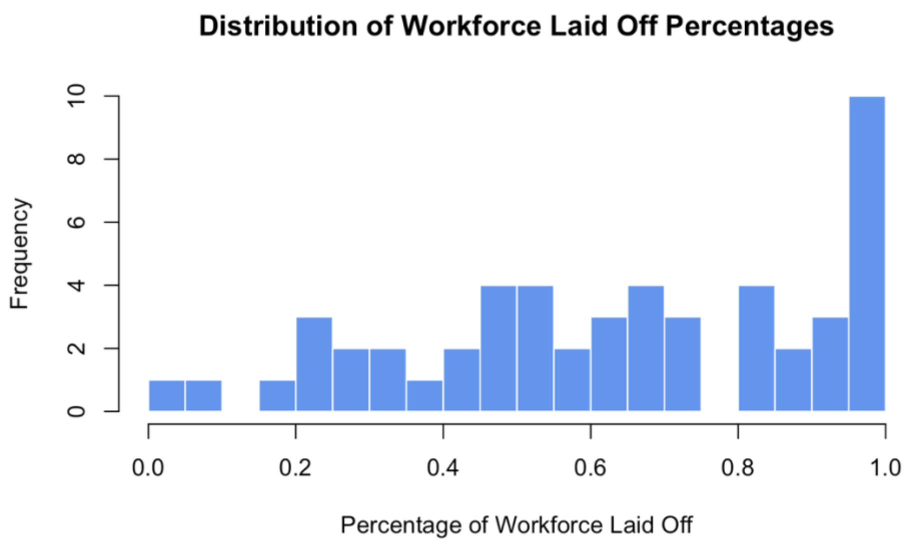

Figure 8 Distribution of Layoff Ratio

The figures 7 and 8, however, do not show the countries that remain completely unaffected by the transition shock. In total, 29 countries, for example Norway, Namibia, and Thailand, are untouched by workforce reduction, as these countries already operate mainly with low carbon EAF technologies. While the combined workforce of these plants accounts for only 2.7% of global steel employment, their resilience underscores how some nations can already mitigating the social risks associated with transitioning the steel sector.

On the other hand, we need to acknowledge the positive shocks a transition in the steel sector can have, by creating new job opportunities. The figure 9 below highlights positive workforce shocks in steel plants globally, showing the number of jobs gained in the transition process. The color gradient indicates the magnitude of the workforce increase, ranging from green (lower gains) to blue (higher gains), while the size of the circles corresponds to the absolute number of new jobs created.In total 204,163 jobs are created due to the transition. These new jobs are related to the announcement of new capacity additions or switches of technology production proccesses.
Several observations stand out. The most significant positive shocks are concentrated in parts of Asia, particularly India and China, where the largest workforce gains are recorded. A few notable plants in the Middle East and Eastern Europe also show substantial increases, with blue circles indicating gains of over 6,000 jobs.
While the majority of positive shocks are smaller, represented by green and light grey circles, these workforce gains are more widely distributed across continents. Regions such as Africa, South America, and North America show only moderate increases, which still however demonstrates a somewhat global trend of job creation in the steel industry, albeit on a smaller scale.
This map underscores how certain regions are experiencing workforce expansion due to technological advancements or capacity increases, in contrast with the heavy layoffs observed elsewhere. The geographic distribution of these positive shocks suggest that some countries are better positioned to adapt and grow their workforce during the transition.

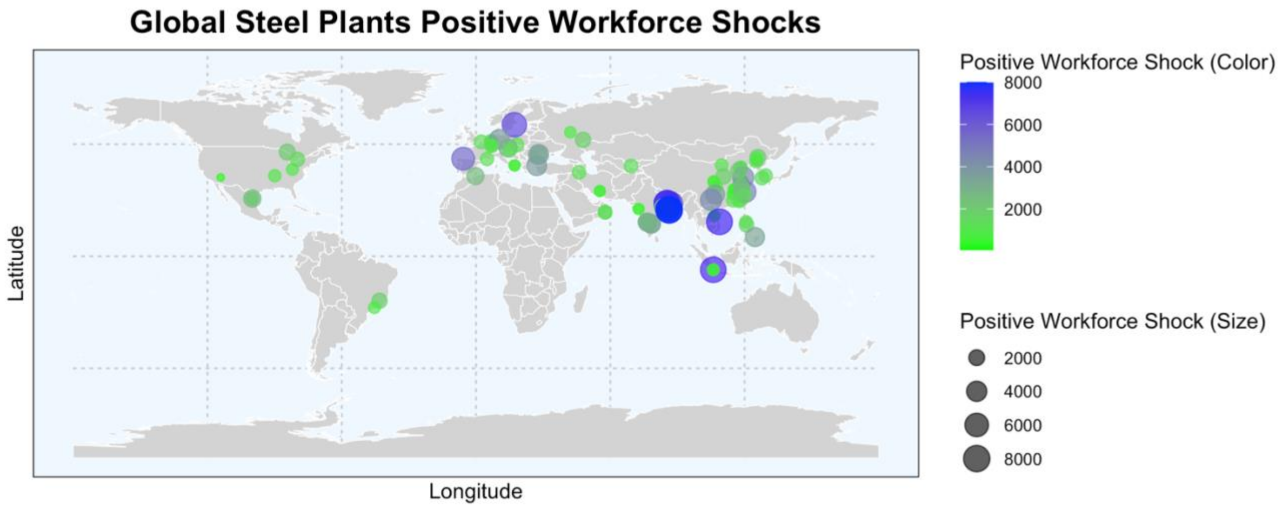

Figure 9 Plant location and added workforce

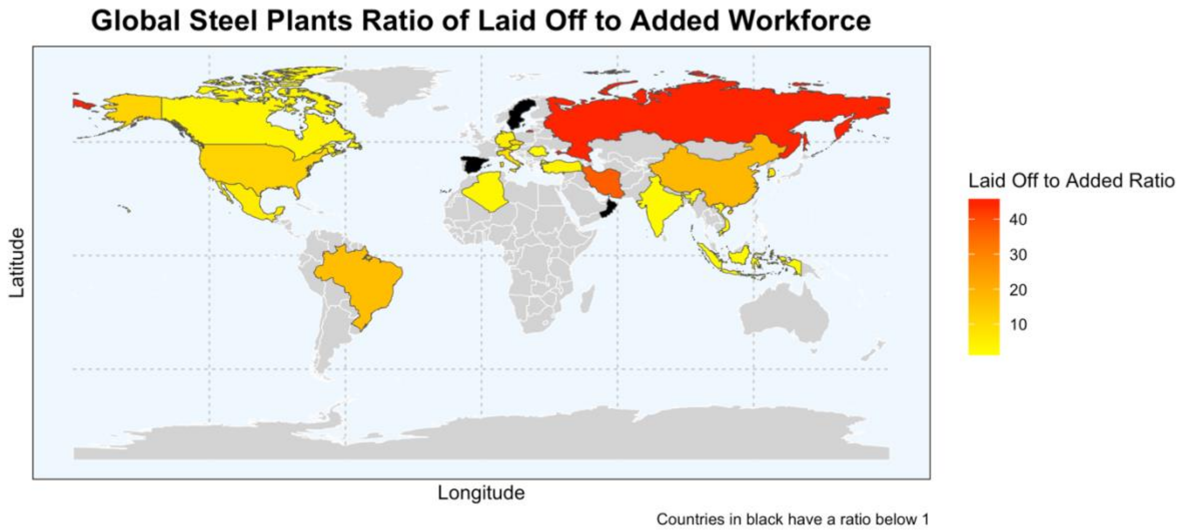

Figure 10 Ratio of Layoffs vs Additions

The map depicted in figure 10 displays the ratio of laid-off workers to newly added workforce across global steel plants. The color gradient highlights the severity of the imbalance, with darker red indicating higher ratios of layoffs relative to workforce gains, while yellow indicates lower ratios. Countries shown in black are those with a ratio below 1, meaning they gain more jobs than they lose.

A few critical patterns emerge. Russia, along with parts of Eastern Europe and Central Asia, exhibits the highest ratios, with values exceeding 40. This indicates substantial workforce losses with little to no job recovery.

In contrast, countries in Southeast Asia, and parts of Africa demonstrate comparatively lower ratios, shown in yellow. This suggests a more balanced transition where workforce losses are partially offset by job gains.

In the black-highlighted countries, such as Spain and Sweden, workforce additions exceed layoffs. These regions showcase how their strategies can mitigate social risks and even create net workforce gains during the transition.

BOX 1: Detailed look into the largest steel producers

When examining the three largest steel producers—China, Russia, and India—distinct differences in workforce impacts become visible. The main social risk results can be seen in the table 2.

Country	Total Workforce	Total Layoffs	%-Layoffs	Total Additions	%-Additions	Laid off / Additions
China	1,017,867.74	- 828,945	81%	45,214	4%	18.3
Russia	244,138.93	- 114,298	47%	2,500	1%	45.7
India	231,505.43	- 195,489	84%	71,971	31%	2.7

Table 2 Main Results for China, Russia and India

Previously, we established that in absolute workforce losses, China is by far the most affected, followed by India and then Russia. However, in relative terms, Russia is losing around 47% of its workforce, a much smaller proportion compared to China's 81% and India's 84%.

The relative shock is partially mitigated in China and India due to planned additions in new capacity or transitions to alternative technologies. While China is adding 72,000 new jobs and India 45,000, Russia is only projected to add 2,500 jobs. This stark difference creates a significant deviation in the ratio of laid-off workers to new workforce additions, as reflected in the figure 10 and the table. Despite the high absolute losses in China and India, their efforts to expand capacity or shift technologies provide some relief, whereas Russia's faces an initial lower relative reduction in its total workforce, but does not plan to enact many additional transitional actions in the future.

Shock Timing

The final aspect to consider is the timing of the layoffs. Figure 11 illustrates the annual timeline of plant shutdowns, while figure 12 highlights the corresponding layoffs per year. While a few isolated plants close before 2030, the most significant workforce reductions are concentrated in 2040 and 2041. During these years, maintaining profitability for BOF steel plants becomes unsustainable, triggering a sharp spike in layoffs.
This concentrated timing is particularly important, as it suggests that the transition shock is not evenly distributed over the coming decades. Instead, it is likely to occur in a sudden and intense surge, which could amplify social stress due to the rapid and widespread rise in unemployment.

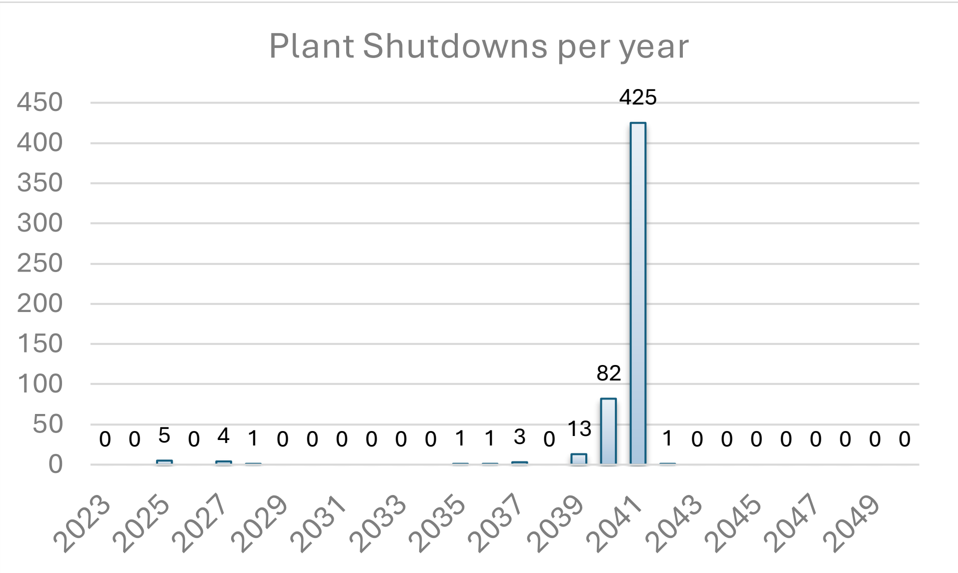

Figure 11 Plant shutdowns per year

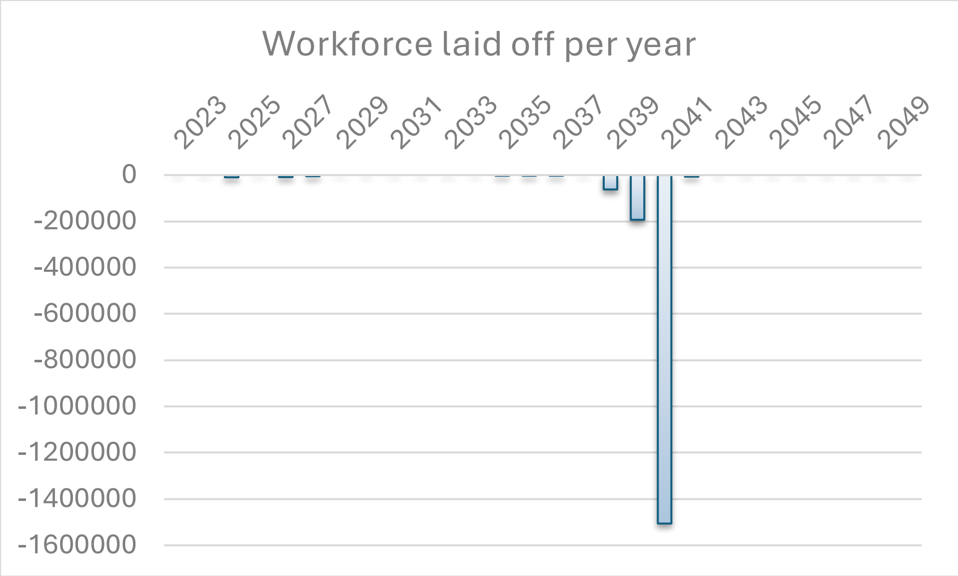

Figure 12 Layoffs per year

Impacts of a carbon tax

A carbon tax can be introduced to observe its effects on the social risk results. For an initial analysis, we can set the carbon tax at a relatively low rate of \$50 per ton of CO_2, implemented in 2030 and increasing by 4% annually.

Important to note is that the initial workforce layoffs and additions remain unchanged, regardless of the carbon tax. For workforce additions, this outcome makes sense intuitively because the carbon tax primarily impacts high-emission technologies, such as BF-BOF. Most new plants being planned focus on technologies using EAF, which are significantly lower in their emission intensity.

For workforce layoffs, however, the reasoning is slightly different. In practice, most BOF plants, the main source of layoffs, are already on a trajectory to be phased out, with or without the carbon tax. This makes sense, given that production relying on high-emission technologies should be phased out to align with decarbonization goals. Therefore, implementing a carbon tax does not change whether high-emission technologies will be phased out, it only influences the timing.

From a technical perspective, a carbon tax could induce an earlier phase-out if profits for these plants drop to zero sooner. In this model, we deduct the carbon tax from revenues and then apply the NPM. However, the \$50 carbon tax, even as it increases over time, does not significantly alter social risk results. While it impacts the transition risk valuation of steel companies by reducing profits, it does not shift the phase-out year earlier.

A higher carbon tax would create a more pronounced impact. Company profits would be further strained, potentially leading to earlier layoffs. This scenario introduces two key consequences. First, earlier layoffs extend the period during which displaced workers remain unemployed, placing additional strain on the labor market. Second, if a carbon tax compresses the transition timeline for companies, the resulting workforce reductions become more concentrated within a narrower window. This accelerates labor loss spikes, intensifying social risk factors and placing further pressure on local economies.

Box 2: Impacts of the Carbon Tax on Phase-Out Timing

The carbon tax can significantly affect the timing of a plant's phase-out. Lets look at one example with Shanxi Gaoyi Steel Co., Ltd., a BF-BOF steel plant in China. The plant has a steel production capacity of 4,500,000 tons and is the largest employer in the GEM database, with a workforce of 36,115, and with that a major catalyst of social risk. Without a carbon tax, the company is projected to reach zero profits by 2041, which would result in the loss of these 36,115 jobs at that time. However, if a carbon tax is implemented at a sufficiently high level, the company could go out of business much earlier. For instance, with a carbon tax set at $560 per ton, which is a high estimate but still within the range of academic discussions around carbon taxes and the social cost of carbon (National Bureau of Economic Research, 2024), the company would shut down as early as 2030.

Limitations

Before concluding this analysis, it is important to ackknowledge the limitations of our approach.First of all, several assumptions were made during the wrangling process, which introduce uncertainty into the results. For instance, workforce estimates, when not provided by GEM, are based on a regression model, where some coefficients are not highly significant. This affects the precision of workforce projections. Moreover, the analysis does not account for potential gradual workforce adjustments that could occur due to declining profits over time. Instead, it relies on a single point in time when the workforce is assumed to be laid off, which simplifies a potentially more complex reality.

Additionally, capacity and emission factors are derived from satellite data provided by Climate Trace. While this is a useful source, it may not always offer the most accurate or precise estimates.

Finally, using the TRISK Model for the steel sector also presents unique barriers. Steel production often carries significant political importance, especially in countries with only one or two domestic steel plants. In such cases, plants might continue operating even when they are economically inefficient, driven by political considerations or national interests. Subsidies further complicate this picture. Governments may step in to support steel plants, delaying closures or help transitions to green technologies. For example, the German government recently provided a 2 billion euro subsidy to Thyssenkrupp's TKH2Steel decarbonization project (Thyssenkrupp, 2023). Such interventions can slow phase-outs, and alter workforce impacts. More research and work is needed to adress these limitations. An initial concept on how these limitations could be adressed is highlihgted in the section "An alternative approach".

Conclusion Social Risk

This section showcased the the methodology for a Social Risk Model building upon a steel sector stress test. Our findings show that jobs in the steel sector are extremely at risk. The current announcements for green steel plants are insufficient to offset the scale of workforce layoffs that could occur in the wake of a transition to a low carbon economy, with the exception of steel production in Oman, Sweden, and Spain. The total workforce facing layoffs amounts to **1,795,060**, while the total workforce additions only reach **204,163**. In absolute terms, the most affected countries are China, Russia, and India,

which collectively experience the highest number of job losses. However, in relative terms, several smaller countries are even more severely impacted, as they lose nearly their entire steel sector employment.
This situation underscores a significant social risk. Large-scale job losses place strain on labor markets, local economies, and communities, particularly in regions heavily reliant on steel production. The consequences could include long-term unemployment, economic stagnation, and increased inequality, all of which increase social instability. From a climate perspective, this challenge highlights the difficult balance between transitioning to low-carbon production and mitigating the social impacts of that transition. While phasing out high-emission technologies like BF-BOF is necessary to meet global climate targets, the resulting workforce disruptions represent a clear social risk. This risk is intrinsically tied to climate change, as the urgency to decarbonize industries accelerates phase-outs and leaves many workers and economies vulnerable without adequate planning for a just transition.
Addressing this dual challenge, climate mitigation and social protection, requires awareness of these issues and a coordinated approach.

The just mentioned methodology showed the data and intution behind the social risk model using steel. Nevertheless, the mentioned social risk methodology can also be applied to other sectors. We can follow the same data structure and by matching employment data from GEM to our existing stress test sectors, we can estimate social risk not only for steel, but also for power, coal and oil & gas.

An alternative approach

To adress the previously mentioned limitations, we have also thought about potential alternative model approaches to capture social risk within the steel sector.

The defined approach is highlighted in figure 13.

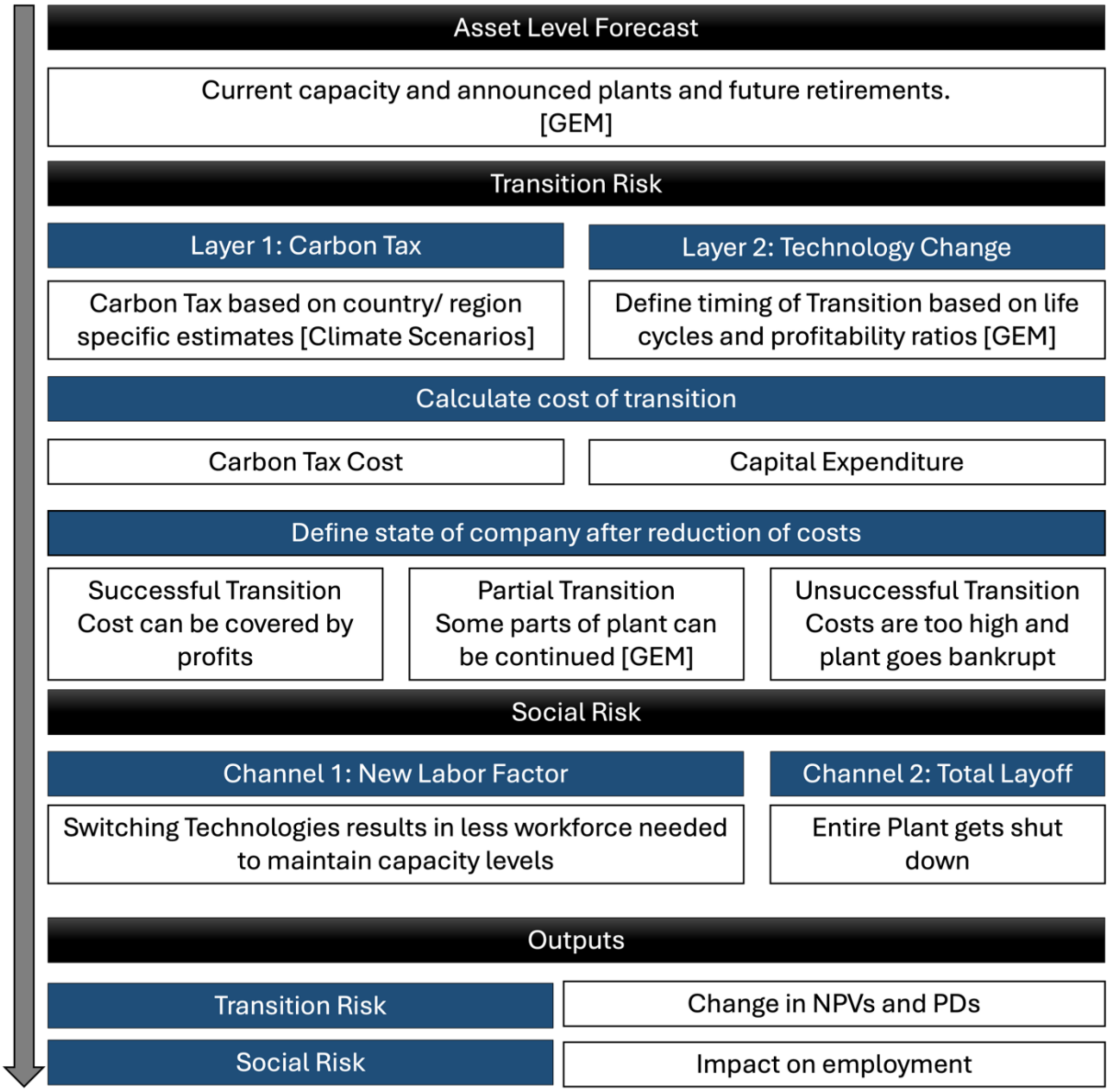

Figure 13 An alternative approach to capture social risk within the steel sector

This alternative approach captures a deviation from the original TRISK model. The method works as follows.

1. **Asset Level Data:** The asset level data is generated and wrangled from GEM as mentioned in previous sections. However, we here focus on capturing a longer time frame, until 2050. This allows us to create a longer forecast, without using scenario based trajectories. The GEM data on retirements and new plant start dates also goes often much longer into the future than the original 5 year forecast we are using in the TRISK model
2. **Transition Risk Assessment:** The Transiton risk assesmet in this approach would work differently, by not focusing on a change in production levels, but rather by increasing the importance and effect of the carbon tax channel, as well as a technology switch channel. The carbon tax channel can be applied on the asset level forecasted revenues. Carbon Tax estimates can be delivered for different geographies form climate scenarios and using a carbon tax will increase pressure on high emitting

companies and create financial stress. The technology change channels works in combination with this stress. When the financial burden of the tax becomes too high, the company will be incentivized to invest and switch to low emitting technologies. Using predefined financial ratio thresholds, we can thus calculate the timing of transition. This can also be enhanced by taking into account life cycle data for specific plants, made available by GEM, which can influence an earlier timing, for example if a high emitting asset needs to be refurbished anyways, which creates signficant costs on its own. The cost of the transtion risk can then be defined as the carbon tax that is applied on the emissions, as well as the capital expenditure to potentially transition to a low emission technology. The capital expenditure can be drawn from different academic sources (DIW Berlin, 2024). For an initial analysis, we would always assume that the company aims to uphold the currently impelemented steel capacity with new technologies. This leaves then three different states a company can enter, based on the associated cost of the transition and the financial conditions of the company

   a. Succesfull Transition: If the company is forced into changing technologies, but has sufficient funds for the capital expenditure, the company has a succesfull transition. Sufficient funds can be defined by taking the overall capital expenditure required to maintain current capacities and comparing these to the available cash flow in the year of transition. Overall, the company still has to face the cost of transition, but at this stage, it will have implemented new technologies which reduces the stress of the carbon tax in following years.
   b. Partial Transition: If the company operated for example using multiple furnaces, it might decide to changing the production process in some of them, while shutting the rest down. This will also reduce the stress from the carbon tax, but will leave the company at a worse state than before, given the lower production capacity and thus lower profits.
   c. Unsuccesfull Transition: If the company is unable to finance the transition, it will be forced to go out of business.

3. **Social Risk**: We can define social risk here similarly to the previous approach, by focusing on the adjustments in workforce, but split up into two different channels using this approach. The first channel for social risk is related to a succefull or partial successful transition resulting in a switch of technology,. When operating with EAFs, a plant requires less labour to produce same levels of capacities than using BOFs (Financial Times, 2024). This means that switching technologies already has a social risk impact by reducing the total workforce in the steel sector. The second channel is linked to the unsuccefull transition, which again means the plant has to shut down and the entire workforce is laid off.
4. **Outputs:** The final outputs that can be generated using this alternative approach are twofold
   a. Transition Risk: For transition risk, the outputs would be the change in the NPV, based on the one hand on the forecast from GEM with and without the cost of the transition. These changes in NPV can then be used to estimate also credit risk changes.
   b. Social Risk: The social risk outputs are the cumulative losses in employment through the two channels .

Advantages and drawbacks of the altnerative model approach

This alternative approach offers several advantages. First, there is no immediate or gradual reduction in production, as is the case with TRISK. The shock is not driven by policy implementation, except for the introduction of a carbon tax, which individual assets must address based on their financial condition. This might be more realistic for certain sectors. Second, this approach introduces capital expenditures into the equation, which is a major aspect that is not covered in TRISK. Third, the approach, similar to TRISK, allows for a large degree of flexibility. This includes setting the level of the carbon tax, but also allowing the introduction of other additional parameters, such as level of subsidies assumptions, which would affect the cost of the transition channel. Finally, this approach allows for extreme granularity. The transition can be measured at the level of individual furnaces, while also considering the overall investment cycle of a plant.

One drawback of this approach is the required data quality. It relies heavily on data provided by GEM, but also other assumptions such as accurate steel prices and capex estimates. Additionally, certain assumptions must be made regarding the timing of the transition and when it becomes financially feasible. While these assumptions introduce some uncertainty into the model, they also allow for a hands-on approach, offering flexibility to adjust parameters and core model settings and test sensitivities.

Part 2: Nature Risk

Introduction: Nature Risks

Nature risk refers to the potential negative impact on businesses, financial systems, or the economy arising from the degradation of ecosystems and the loss of biodiversity. Ecosystem services and biodiversity is often considered in conjunction. All ecosystem services depend on the functionality and ecological productivity of the ecosystem providing the service. Biodiversity, a measure of the variation of life forms at genetic and species level, forms a critical part of ecosystem functionality. However, ecosystem services can also be impaired by nature losses or resources stresses. From the perspective of financial risk, ecosystem services are of more direct interest than biodiversity as it more broadly captures nature risks and more directly relates to the risk transfer mechanism. In other words, biodiversity loss is a risk driver and the ecosystem service is the risk transfer mechanism.

Economic activity relies on inputs – labor, capital, land, and entrepreneurship – all of which depend on ecosystem services. Put simply, humans need breathable air and water to work and grow crops. Despite this, ecosystem services have traditionally been underappreciated in economic analysis, particularly in developed economies where their decline has been subtle or indirect. However, they are as foundational to production as energy.

Ecosystem services interact with economic inputs in three ways:

1. **Direct Input:** Services like water are essential for production, and their decline directly impacts output.
2. **Enabler:** Services such as waste decomposition to ensure resources like clean water remain available for use.
3. **Facilitator:** Healthy ecosystems enhance productivity by supporting mental health and well-being.

Referring back to the function of inputs of economic activity, nature risks can affect those in the following ways:

1. **Labour:** Ecosystem services provide air, water, food, and the environment in which humans live. A decline in ecosystem services can thus both directly kill labour (e.g. radiation from a nuclear disaster); reduce productivity (e.g. disease prevalence); or remove labour through social dislocation (e.g. toxic water requires resettlement, change in climatic conditions requiring resettlement).
2. **Capital:** Ecosystem services may both directly act as capital (e.g. water) or – similar to labour – destroy capital through a decline in the ecosystem service provided.
3. **Land:** Land is directly an ecosystem service as an input into production.
4. **Entrepreneuership:** Ecosystems inspire innovation, such as biomimicry in aviation or materials science. While their decline may not immediately halt entrepreneurship, reduced cultural and supporting services can diminish well-being and creativity, potentially impacting innovation in the long term.

With the introduction of nature risk, it is also improtant to add its distinction to the concept of transition risks. Nature risks stem from the physical loss or degradation of natural systems, posing immediate threats to economic stability. Transition risks are a byproduct of the response to these environmental challenges, representing the cost of adapting to a more sustainable economy. Together, they highlight the dual challenge of mitigating environmental harm while navigating the economic shifts required to address it.

In this part of the report, we highlight the methodology of four different ways to measure the effect of nature risk, using different nature risk concepts and philophies. The different concepts are Willingness to Pay, Planetary Boundaries, Land use, and Macro. For the first three, we have also created a designated excel valuation tool to help third parties with the ecosystem cost assessment.

Box 3: Main characteristics of 1in1000 Nrisk Excel Assessments

Our excel assessment tools for Nrisk valuation are all based on a similar structure.

At their core is the calculation of **revenues**, which can be expressed as a total figure or derived from production output and unit prices. These revenues are projected over time using a baseline **growth rate** to reflect status quo conditions.

The **profits** are calculated based on revenue at time t for company i and a defined Net Profit Margin (NPM) for company i, which represents the proportion of revenue that translates into profit.

$$Profits_{t,i} = NPM_i * Revenue_{t,i}$$

These profits are adjusted for the time value of money using a discount rate r, ensuring that future profits are appropriately reflected in today's terms.

$$Discounted\ Profits_t = \frac{Profits_t}{(1+r)^t}$$

For longer-term valuations, the tool can include a terminal value TV, which accounts for the business's value beyond the forecast period. Ecosystem costs can then take form by adjusting the baseline growthrate, the total output or revenues, or the cost structure. We also include a shock year, which signals the timing of when ecosystem costs emerge. This can happen either in the start year of the analysis or at any point in the future.

The final step is the calculation of the NPV which aggregates all discounted profits in the baseline scenario, and in the adverse scenario. By comparing the NPV under baseline conditions with that in an adverse scenario, including the costs associated with nature-related risks, the excel quantifies the financial impact of these risks on the business.

$$NPV_{scenario} = \sum_{start\ year}^{end\ year} \frac{Profits_{t,\,scenario}}{(1+r)^t} + TV$$

Concept 1: Willingness to Pay

The concept of Willingness to Pay (WTP) is rooted in the philosophy that the costs of nature-related risks are reflected in what people are willing to pay for ecosystem services. This approach relies on data provided by the Ecosystem Service Valuation Database (ESVD), which focuses on compiling economic welfare values associated with ecosystem services. The database covers a variety of ecosystem services and is freely accessible[5].

The ESVD enables the direct use of WTP measurements or, alternatively, the creation of a percentage share of ecosystem costs per output relative to total costs per output. The main intuition behind this concept is that WTP reflects changes in the cost structure for firms or businesses, rather than changes in their total output volume.

For WTP we are using the input variables as indicated in table 3, which can be varied based on the users preferences and information about a specific company or ecosystem service.

Valuation Parametes (INPUT TABLES)

Total revenues	100.00 €
Net Profit Margin	4%
Dependency / Externality?	7.3%
Share of ecosystem cost internalization by producer	5%
Growth Rate	3%
Discount Rate	2%
Shock Year	2028

Table 3 WTP Valuation Parameters

The parameters show among others the dependency, which is the WTP for a specific ecosystem, here highlighted as a ratio of the cost per unit and the internalization by producer, which depicts how much of the total WTP cost a firm has to cover.

By multiplying both parameters we get the cost adjustment that a company has to face, which in this case is 0.37%. We can deduct this value from the overall net profit margin to internalize these additional cost in an adverse scenario state. The shock year indicates the year when the adverse scenario uses the adjusted NPM. Before that, the adverse and baseline scenario are the same. By aggregating the discounted profits in the baseline and adverse scenario, we can create different NPVs.

The overall results of this exercise and the financial impact of this ecosystem shock concept are shown in the table 4.

[5] To access the database, you can use this link: https://www.esvd.net/

Valuation Overview (Output tables)	
NPV - Baseline	128.16 €
NPV Shock (applied on revenues)	118.33 €
NPV - Shock (in %)	-8%

Table 4 WTP Valuation Overview

Concept 2: Planetary Boundary

The second concept captures the logic of limited availability of ecosytem services. Within planetary boundaries, we assess the costs of the depletation of a specific service, which results in limited use of this service for a company, no matter what they would be willing to pay for it. A good case study is by refering here to the fishing sector.
In contrast to WTP, this concept focuses on changes in output volumes and ignores changes in cost structures. Table 5 shows the input parameters for planetary boundaries. The main indicator for this ecosystem cost is the use of an alternative growth rate. In contrast to a defined status quo growth rate of 4% in the fishing sector, overfishing and resource deplation may result in a decline in outputs. This is based on data provided by PlanetTracker (Planet Tracker, 2024).

Valuation Parametes (INPUT TABLES)

Baseline Fishing Revenue	100.00 €	*based on PlanetTracker data*
Net Profit Margin	4%	
Alternative growth rate	-1%	
Baseline Growth Rate	4%	
Discount Rate	0%	
Shock Year	2025	

Table 5 Planetary Boundaries Valuation Parameters

Using the parameters, defined in the input table we can calculate the baseline and adverse revenue pathway and consequently transform them into discounted net profits over time, shown in table 6.

Year	Revenue	Alternative Revenue pathway	Discounted Baseline Profit	Discounted Shock Profit (cost applied on Revenue)
2022	100.00 €	100.00 €	4.00 €	4.00 €
2023	104.00 €	104.00 €	4.16 €	4.16 €
2024	108.16 €	108.16 €	4.33 €	4.33 €
2025	112.49 €	107.08 €	4.50 €	4.28 €
2026	116.99 €	106.01 €	4.68 €	4.24 €
2027	121.67 €	104.95 €	4.87 €	4.20 €
2028	126.53 €	103.90 €	5.06 €	4.16 €
2029	131.59 €	102.86 €	5.26 €	4.11 €
2030	136.86 €	101.83 €	5.47 €	4.07 €
2031	142.33 €	100.81 €	5.69 €	4.03 €
2032	148.02 €	99.80 €	5.92 €	3.99 €
2033	153.95 €	98.81 €	6.16 €	3.95 €
2034	160.10 €	97.82 €	6.40 €	3.91 €
2035	166.51 €	96.84 €	6.66 €	3.87 €
2036	173.17 €	95.87 €	6.93 €	3.83 €
2037	180.09 €	94.91 €	7.20 €	3.80 €
2038	187.30 €	93.96 €	7.49 €	3.76 €
2039	194.79 €	93.02 €	7.79 €	3.72 €
2040	202.58 €	92.09 €	8.10 €	3.68 €
2041	210.68 €	91.17 €	8.43 €	3.65 €
2042	219.11 €	90.26 €	8.76 €	3.61 €
2043	227.88 €	89.36 €	9.12 €	3.57 €
2044	236.99 €	88.46 €	9.48 €	3.54 €
2045	246.47 €	87.58 €	9.86 €	3.50 €
2046	256.33 €	86.70 €	10.25 €	3.47 €
2047	266.58 €	85.84 €	10.66 €	3.43 €
2048	277.25 €	84.98 €	11.09 €	3.40 €
2049	288.34 €	84.13 €	11.53 €	3.37 €
2050	299.87 €	83.29 €	11.99 €	3.33 €
TV	-	-	-	-

Table 6 Planetary Boundaries Revenues and Profits over time

The final results are shown in table 7. We can compare the total production volume in 2050 for the baseline and adverse state. In this example, production has been reduced dramatically, covering only 29% of the baseline total. In terms of the financial valuation, the effect of planetary boundaries in this case would result in a reduction of the NPV of nearly 50%.

2050 Relative Production volume	
Production in 2050 relative to baseline	29%

Valuation Overview (Output tables)	
NPV - Baseline	211.87 €
NPV - Shock (applied on revenues)	110.98 €
NPV - Shock (in %)	-48%

Table 7 Planetary Boundaries Valuation Overview

Concept 3: Land

The third concept is based on the specific ecosystem cost for Land. This is in essence a similar philosophy as concept 1 WTP, but focused on a specific sector. Concept 3 Land also prioritizes changes in the cost structure, while leaving initial revenue or outputs untouched. The ecosystem cost per hectare can again be informed by ESVD, or alternatively as done in this case, by using data provided by the Inevatible Policy Response (IPR) (IPR, 2024).

Table 8 shows the input paramters for Land. We are using a 88 € ecosystem cost per hectare (willingness to pay) from IPR. Moreover, we are using an ecosytem cost internalization, which we set at 50%. This implies that 50% of the total ecosytem costs have to be internalized by the firm, while the other 50% can be moved through to the final consumers. Finally, we also use a specific profit adjustment of 80%, which means that the NPM is also going to be reduced by 20%. We added this additional channel to acount for any compounding profit adjustments not taken into consideration in the intial ecosystem cost metric, however leave it up to the user to decide if they want to keep this adjustment.

Valuation Parametes (INPUT TABLES)	
Revenue per Hectare	130.00 €
Net Profit Margin	44%
Ecosystem Cost (from IPR)	88.00 €
Ecosystem cost internalization	50%
Growth Rate	4%
Discount Rate	0%
Shock Year	2025
Profit adjustment	80%

Table 8 Land Valuation Parameters

The main model methodology for concept 3 uses the same revenues and growth rates for baseline and adverse scenario. After the shock year, the model introduces the ecosystem cost per hectare for the adverse scenario. The cost per hectare are calculated by multiplying the ecosystem cost with the cost internalization ratio. We deduct the cost per hectare from the revenues per hectare and only then apply the NPM. Following this, the final steps are as usual by discounting profits and aggregating them for the NPVs.

Table 9 shows the final results for Land. The profits per hectare showcase the initial adjustment in profits based on the internalized ecosystem costs. The Valuation overview shows then the total NPV shock by introducing this nature risk.

Profit per year per Hectare Overview (Output Tables)	
Profit per Hectare - Baseline	57.20 €
Profit per Hectare - Shock	37.84 €
Profit per Hectare - Shock (in %)	-34%

Valuation Overview (Output tables)	
NPV per Hectare - Baseline	3,029.67 €
NPV per Hectare - Shock (applied on revenues)	2,056.76 €
NPV per Hectare - Shock (in %)	-32%

Table 9 Land Valuation Overview

Concept 4: Macro

The final concept is a more macroeconomic approach to nature risk. Climate stress tests often rely on third party climate scenarios, provided for example by the Network for Greening the Financial System (NGFS) and their “Hot House” scenarios. However, this approach presents several challenges. The scenarios by the NGFS represent a central estimate for a high-carbon future but do not account for more pessimistic outlooks that predict significant economic dislocation resulting from higher temperature outcomes. Moreover, they focus exclusively on direct climate impacts, leaving out potential ecosystem shocks that could arise due to climate change.

Theia Finance Labs published a report in March 2024 to analyse the potential underestimation of risk by not including ecosystem risks and other tipping points (Theia Finance Labs, 2024). The report’s methodology to estimate this underestimation does not provide a fully developed, integrated economic model, but instead, it utilizes a simple GDP and discounted cash flow model that incorporates shocks based on estimates of economic impacts from various climate-related tipping points. These estimates are sourced from third-party literature. The aggregated effects are then integrated into a global discounted cash flow model, which seeks to estimate future asset value losses in terms of today's net present value. This straightforward approach allows for isolating the effects of different potential tipping points and ensures the findings are communicated clearly.

Two baseline scenarios are used in the analysis, one from Swiss Re from 2021 (SwissRe, 2021) and the 2 Degree Investing Initiative (2DII) stress-test scenario baseline from 2019 (2DII, 2019). Swiss Re's 2021 research provides baseline GDP impacts of climate change by 2050, based on an estimated warming of 2.3°C.

For ecosystem tipping points, projections are drawn from WWF (WWF, 2020) and World Bank data (World Bank, 2021). While WWF's estimates are more conservative, the World Bank's projections only extend to 2030, requiring assumptions about a policy response beyond this point. To maintain consistency, the analysis assumes the effects measured by the World Bank unfold over a longer timeline, up to 2050. This more conservative assumption allows for consistent and comparable results.

Methodology Deep Dive

1. In the report, we accumulate first the GDP loss inputs from different sources and aggregate them to create a cumulative GDP effect. With this, we take into account not one tipping point, but multiple consecutive ones.
2. The model uses a multi-period discount divident model

$$P = \sum_{1}^{n} (\frac{D^n}{(1+r)^n} + TV$$

P is the share price, D the dividend payout at timer period n, and r the discount rate. The discount rate in the report is based on the US implied market return, based on the market risk premium and the risk free rate, derived from market-risk-premia.com on the 23rd of October, 2023 and set at 7%. The model limit for n is set to 28, assuming that the analysis is conducted between 2022-2050 where 2050=28. The TV is set to 0 for simplicity.

3. We then calculate a GDP for 2050 using a 2022 proxy value of 100 and the different aggregated tipping points. Missing years between 2022 and 2050 are interpolated based on the average yearly growth.

$$g_{shock} = \left(\frac{\left(GDP_{baseline}^{28} * (1 + s)\right)}{GDP_{baseline}^{0}}\right)^{\frac{1}{28}} - 1$$

Where s is derived from the literature and represents the aggregated percentage GDP reduction in 2050 (n=28) for different levels of cumulative tipping points.

4. We can discount the interpolated GDP pathways by using the discount rate and consecutevly aggregate those, as shown in step 2. This creates GDP pathways for both the baseline state and the different scenarios involving additional tipping points or ecosystem losses. Aggregating the discounted cash flows allows to calculate an NPV for the baseline and different adverse states (or share price P). This gives an indication of the potential additional financial risk by taking into account risk factors like ecosystem decline.

The Figure XX below highlights the estimated GDP growth pathways until 2050 under a no climate change baseline and the cumulative effects of climate change, climate tipping points, ecosystem declines, and social risks. The results highlight that the most extreme scenario involves effectively long-term negative growth over the next three decades.

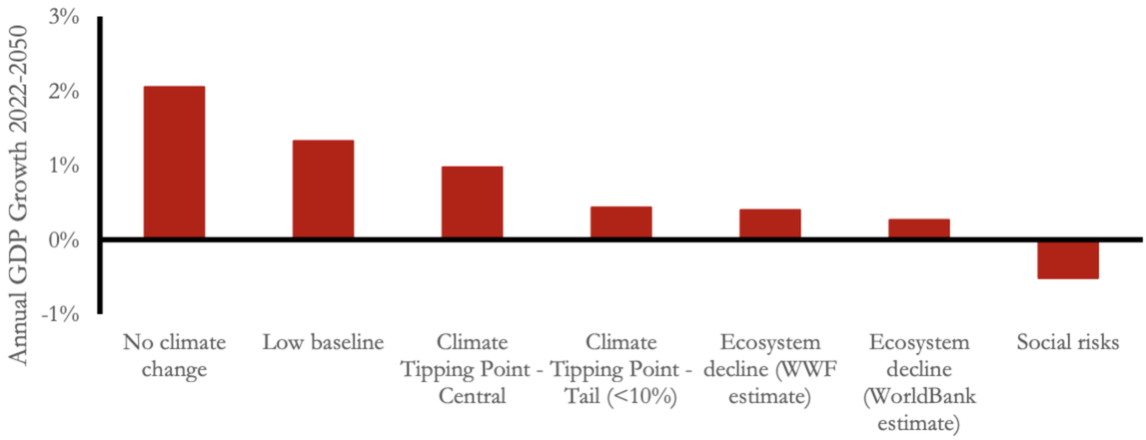

Figure 14 Reduction in GDP Growth based on different tipping points

In term of negative impact on the equity market, as calculated with the NPV comparisons to the Baseline state, our findings in figure XX suggest that translating these losses into absolute values, potential social and ecosystem feedback loops can wipe $31 trillion from global capital markets in terms of lower returns.

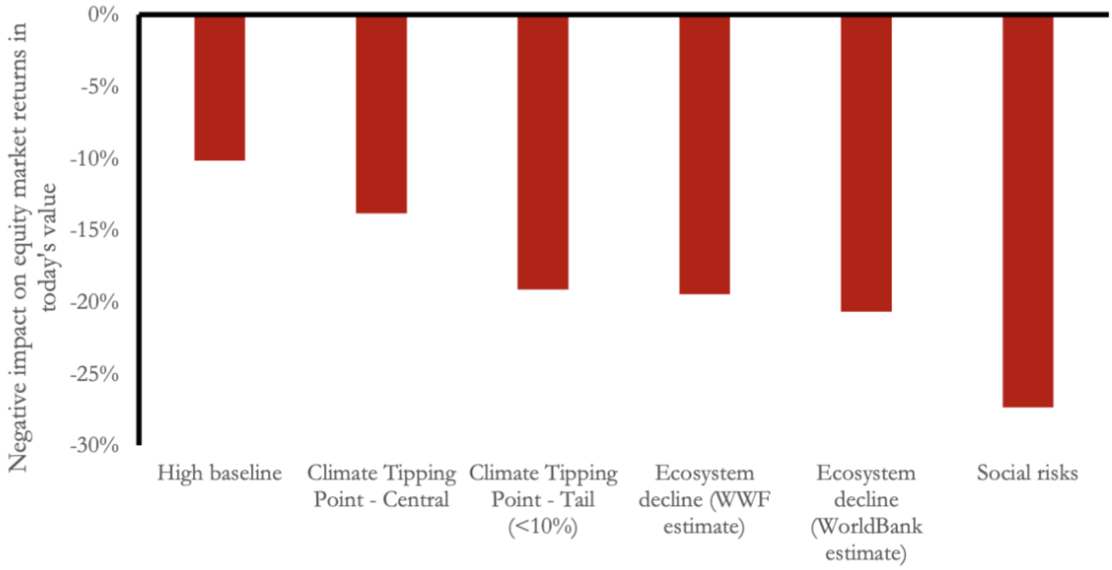

Figure 15 Negative impact on market returns based on different tipping points

Nature Risk was introduces into this analysis by using two different sources, and while its compound effect was not as large as other tipping points, it still showed a significant reduction in GDP growth and market returns, highlighting the dangerous macro ecomomic implications that ecosystem decline can create.

Conclusion Nature Risk

The analysis presented in this part of the report highlights the significant and diverse risks posed by the degradation of ecosystems.. Nature risks, while often overshadowed by more familiar categories like transition and physical risks, are shown to have profound implications for economic stability and financial systems. We use different methodological concepts, like Willingness to Pay, Planetary Boundaries, and macroeconomic assessment, to bridge the gap in valuating the financial impacts of nature risks. These approaches illustrate the costs of ecosystem degradation, both at a firm level and across broader economic systems. The valuation tools developed offer practical ways to quantify these risks and incorporate them into decision-making processes.

Our findings emphasize the urgency of integrating nature risks into financial assessments and stress-testing frameworks on a larger scale. Without recognizing the economic consequences of biodiversity loss and ecosystem decline, financial institutions and policymakers risk underestimating future disruptions. The results of this analysis demonstrate that addressing nature risks is not only critical on an environmental perspective but also a critical step toward ensuring long-term economic and financial resilience.

Bibliography

World Economic Forum. (2023). *Why steel can be an unexpected leader in decarbonization*. From https://www.weforum.org/stories/2023/08/why-steel-can-be-an-unexpected-leader-in-decarbonization/#:~:text=Steel%20is%20the%20planet's%20largest,to%20machinery%2C%20transportation%20and%20energy.

Reuters. (2024). *Thyssenkrupp to cut 11,000 jobs at steel division in major corporate shakeup*. From https://www.reuters.com/markets/commodities/loss-making-thyssenkupp-steel-slash-5000-jobs-by-2030-2024-11-25/

Mission Possible . (2022). *Making Net Zero Steel Possible*. From https://3stepsolutions.s3-accelerate.amazonaws.com/assets/custom/010856/downloads/Making-Net-Zero-Steel-possible.pdf

National Bureau of Economic Research. (2024). *The Macroeconomic Impact of Climate Change: Global vs. Local Temperature*. From https://www.nber.org/papers/w32450

Thyssenkrupp. (2023). *EU Commission approves German federal and state government fund-ing for thyssenkrupp Steel's "tkH2Steel" decarbonization project*. From https://www.thyssenkrupp.com/en/newsroom/press-releases/pressdetailpage/eu-commission-approves-german-federal-and-state-government-fund-ing-for-thyssenkrupp-steels-tkh2steel-decarbonization-project-228875

DIW Berlin. (2024). *evisiting Investment Costs for Green Steel: Capital Expenditures, Firm Level Impacts, and Policy Implications*. From https://www.diw.de/de/diw_01.c.901042.de/publikationen/diskussionspapiere/2024_2082/revisiting_investment_costs_for_green_steel__capital_expenditures__firm_level_impacts__and_policy_implications.html

Financial Times. (2024). *Climate tech explained: low-emission steel plants*. From https://www.ft.com/content/735d00a8-678f-4e0c-8dcc-9d82518299ed

Planet Tracker. (2024). *Seafood Database*. From https://planet-tracker.org/seafood-database-update/

IPR. (2024). *Inevitable Policy Response*. From https://ipr.transitionmonitor.com/

Theia Finance Labs. (2024). *How climate stress tests may underestimate financial losses from physical climate risks by a factor of 2-3x*. From https://theiafinance.org/wp-content/uploads/2024/03/1in1000_finstab_final_v0.pdf

SwissRe. (2021). *The economics of climate change: no action not an option*. From https://www.swissre.com/dam/jcr:e73ee7c3-7f83-4c17-a2b8-8ef23a8d3312/swiss-re-institute-expertisepublication-economics-of-climate-change.pdf

2DII. (2019). *Storm ahead: A proposal for a climate stress-test scenario*. From https://2degreesinvesting.org/wp-content/uploads/2019/02/Stress-test-report_V2.pdf

WWF. (2020). *GLOBAL FUTURES ASSESSING THE GLOBAL ECONOMIC IMPACTS OF ENVIRONMENTAL CHANGE TO SUPPORT POLICY-MAKING*. From https://c402277.ssl.cf1.rackcdn.com/publications/1299/files/original/Summary_Report.pdf?158145625 0

World Bank. (2021). *The Economic Case for Nature*. From https://openknowledge.worldbank.org/bitstream/handle/10986/35882/A-Global-Earth-EconomyModel-to-Assess-Development-Policy-Pathways.pdf?sequence=1&isAllowed=y

Otto, I. M., Reyer, D. R., & Marcus, R. (2017). Social vulnerability to climate change: a review of concepts and evidence. From https://link.springer.com/article/10.1007/s10113-017-1105-9

Carleton, T., & Hsiang, S. (2016). *Social and economic impacts of climate*. From https://www.science.org/doi/abs/10.1126/science.aad9837

Arabadjieva, K., & Bogojević, S. (2024). *The European Green Deal: climate action, social impacts and just transition safeguards*. From https://doi.org/10.1093/yel/yeae004

World Bank. (2023). *Social Dimensions of Climate Change* . From https://www.worldbank.org/en/topic/social-dimensions-of-climate-change

United Nations. (2024). *Five ways the climate crisis impacts human security*. From https://www.un.org/en/climatechange/science/climate-issues/human-security#:~:text=Climate%20change%20increases%20poverty%20and,agriculture%2C%20forestry%2C%20and%20fishery

Habibullah, M. S. (2022). *Impact of climate change on biodiversity loss: global evidence*. From https://link.springer.com/article/10.1007/s11356-021-15702-8

Weiskopf, S. R., Rubenstein, M. A., Crozier, L. G., Gaichas, S., Griffis, R., Halofsky, J. E., . . . Pershing, A. J. (2020). *Climate change effects on biodiversity, ecosystems, ecosystem services, and natural resource management in the United States*. From https://doi.org/10.1016/j.scitotenv.2020.137782

Breeden, S. (2022). *The nature of risk* . From https://www.bankofengland.co.uk/speech/2022/october/the-nature-of-risk-speech-by-sarah-breeden

Green Finance Institute. (2024). *Assessing the Materiality of Nature-Related Financial Risks for the UK*. From https://www.greenfinanceinstitute.com/wp-content/uploads/2024/06/GFI-GREENING-FINANCE-FOR-NATURE-FINAL-FULL-REPORT-RDS4.pdf