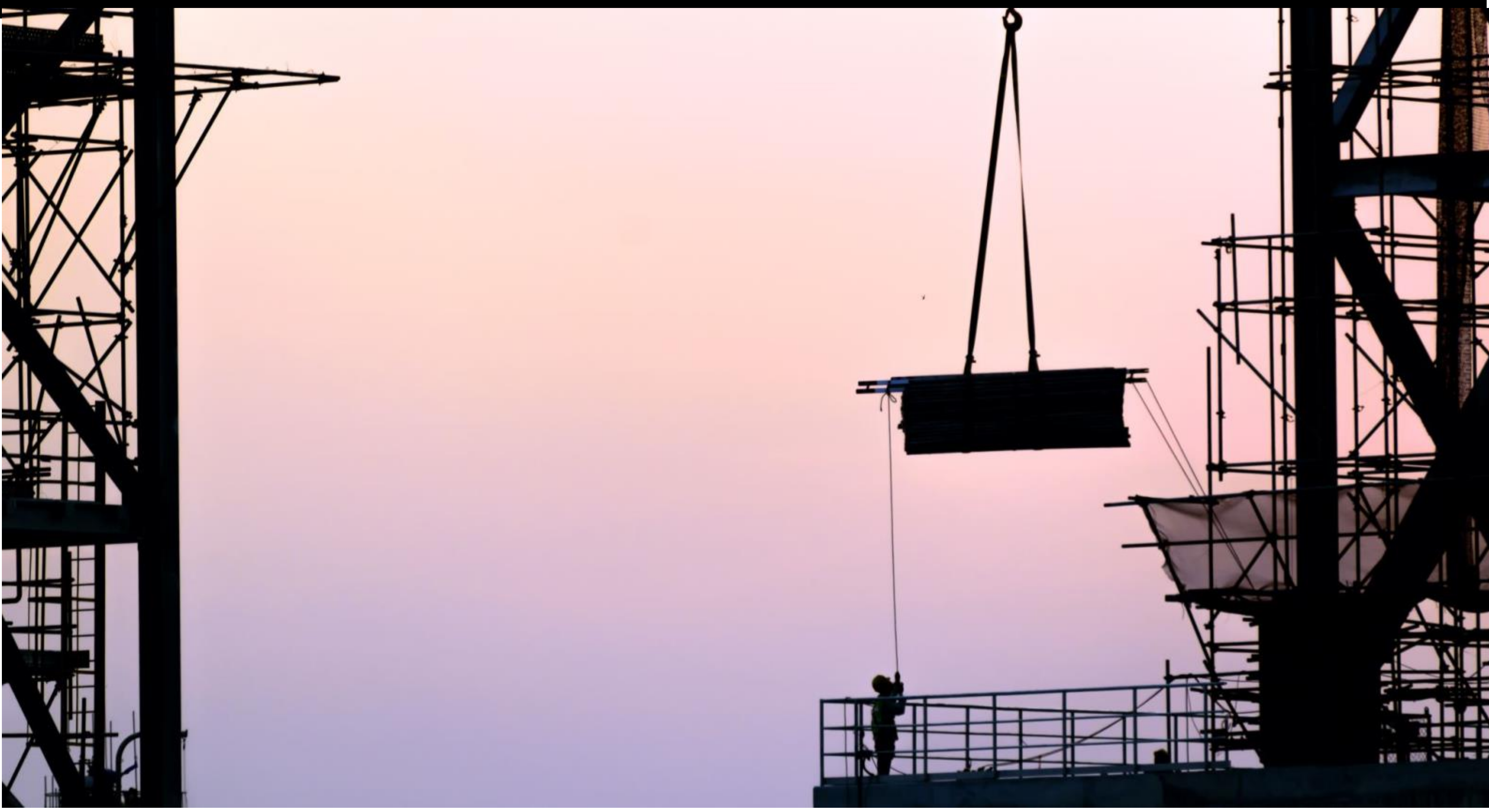
*til*TRISK

Methodology

Q4 2024



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About 1in1000

1in1000 is an initiative of Theia Finance Labs (originally known as 2° Investing Initiative Germany), a German non-profit think tank specializing in the quantification of climate change risks within the financial sector. Since 2023, 1in1000 has become a joint research initiative between Theia Finance Labs and the University of Oxford Sustainable Finance Group. The joint initiative cooperates on expanding research frontiers in climate stress testing and implementing climate stress testing analytical exercises as well as capacity building with supervisors and central banks around the globe. This methodology approach refers to the 1in1000 Trisk model, which is designed as an asset-based forward looking climate transition stress test.

About tilt

Tilt is an independent venture launched by Theia Finance Labs (formerly known as 2° Investing Initiative Germany). The project is funded by the EU LIFE PASTAX grant, financial institutions, and the philanthropic community. Fostering transparency and credibility, tilt's software empowers EU banks to set up impactful climate strategies in SME lending. It's software enables banks to generate climate SME data, explore the results in a comprehensive way, get a climate strategy for their SME lending portfolio and to find the most vulnerable clients to grant effective climate improvement loans.

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1. Introduction

Small and medium-sized enterprises (SMEs) occupy a significant share of the global economy and, in many countries, constitute a vital component of financial markets—particularly where capital markets are less developed. Yet, existing climate stress testing and sensitivity analysis methodologies have traditionally overlooked the potential financial impacts on these smaller businesses. Although many SMEs may not be immediately identified as "climate-relevant" due to their sectors or smaller emissions profiles, their operational resilience is inherently tied to broader economic shifts. Building on previous frameworks developed under ET RISK and LIFE PACTA 2.0, this LIFE STRESS project the extends existing climate stress test models to incorporate the realities of SME operations, aiming to shed light on how they might fare under different transition and physical risk scenarios.

A core piece of this expansion is *tilt*, a methodology focusing on product-level emissions, business types, and location. While *tilt* provides granular emissions data, it does not address factors like a firm's operational transitions or financial resilience under climate stress. To bridge this gap, tilTRISK integrates tilt's SME data with the scenario-based transition risk modeling of TRISK. By evaluating how large firms in climate-critical sectors might experience "late-and-sudden" policy shifts and then projecting these disruptions to SMEs in the same region and sector, tilTRISK offers a comprehensive view of vulnerability. By aggregating these disruptions to the sector and regional levels, tilTRISK infers "spillover" effects for SMEs operating in comparable circumstances. In this way, it becomes possible to capture the often-overlooked vulnerability dimension that extends beyond basic emissions profiles—offering a deeper insight into how an SME's equity valuations and debt obligations may shift under a chosen climate scenario.

The tilTRISK indicators quantify two dimensions of financial risk: 1) market risk (as measured by potential Net Present Value losses under sudden transitions) and 2) credit risk (derived from a structural Probability of Default model). Such insights can then be aggregated to produce portfolio-level risk metrics, enabling banks and other institutions to gauge the climate exposure of their lending or investment portfolios. In this report, we present the underlying methodology for constructing and applying these tilTRISK indicators to transition risks, as well as considerations for physical, ecosystem, and social risks. By integrating SME-specific data, scenario-based financial modeling, and broader risk perspectives, tilTRISK provides a transparent, scalable, and analytically robust toolkit for climate stress testing in the SME segment. Ultimately, these insights seek to empower financial institutions, investors, and SMEs themselves to navigate a rapidly evolving regulatory and market landscape, laying the groundwork for informed decision-making and targeted climate strategies.

Section 2 of this report outlines the background of the research question for why we should build on the tilt database, the motivation doing so, and the outline of the proposed tilTRISK indicators. Section 3 outlines the data, methodology and design of the tilTRISK indicators. Section 4 assesse the first set of results produced on the initial set of covered firms. Section 5 discusses avenues for follow-up research and Section 6 is the conclusion.

2. From tilt to tilTRISK

Source data: tilt database

In this project, we make use of the SME database created as part of the LIFE PASTAX project. This data will provide information on the sector and location of SMEs. In transition risk, this information will be linked with company data from the main climate relevant sectors, for which we can already estimate transition related shocks.

The *tilt* methodology (Transforming in a Low Carbon Transition) methodology developed at Theia Finance Labs proposes two climate indicators for assessing double materiality. This methodology is tailored for SMEs, requiring three data inputs per SME firm: product, business type, and location. The data is developed in a transparent and open-source manner, allowing for independent validation by users, academia, and peers. By focusing on product-specific information, the methodology offers a more granular assessment than industry averages.

Using the methodology, *tilt at* Theia Finance Labs developed a comprehensive dataset covering over 280,000 firms across Austria, France, Germany, the Netherlands, and Spain. It covers firms in the eight most climate-relevant sectors: construction, energy, power, industry, land use, metals, non-metallic minerals, and transport. The dataset was created by web-scraping data on product, business type, and location from a business-to-business website and merging it with climate data from sources like ecoinvent (2024). Sector-specific emission reduction targets from the International Energy Agency (IEA, 2023) and Inevitable Policy Response (IPR, 2023) were integrated. The assessment begins at the product level and is then aggregated to the firm level for firms producing multiple products, based on specific production share assumptions.

The goal of the *tilt* database is to assess climate-related risks in SME portfolios and develop data-driven climate strategies. By linking *tilt* SME data with financial data, users can gain deeper insights into climate transition risks and their portfolio's environmental footprint. In research, the data can help analyse whether financial institutions consider double materiality in their finance and lending decisions, expanding studies beyond equity and syndicated loans to include SMEs (e.g., Sastry et al., 2024; Green and Vallee, 2022; Kacperczyk and Peydró, 2022; Bolton & Kacperczyk, 2022, 2021; Ehlers and Packer, 2022; Carbone et al., 2021). The data also supports regional climate transition analysis and case study selection.

Building on *tilt*

Figure 1 gives an overview of the steps involved to construct the two climate indicators in the *tilt* methodology:

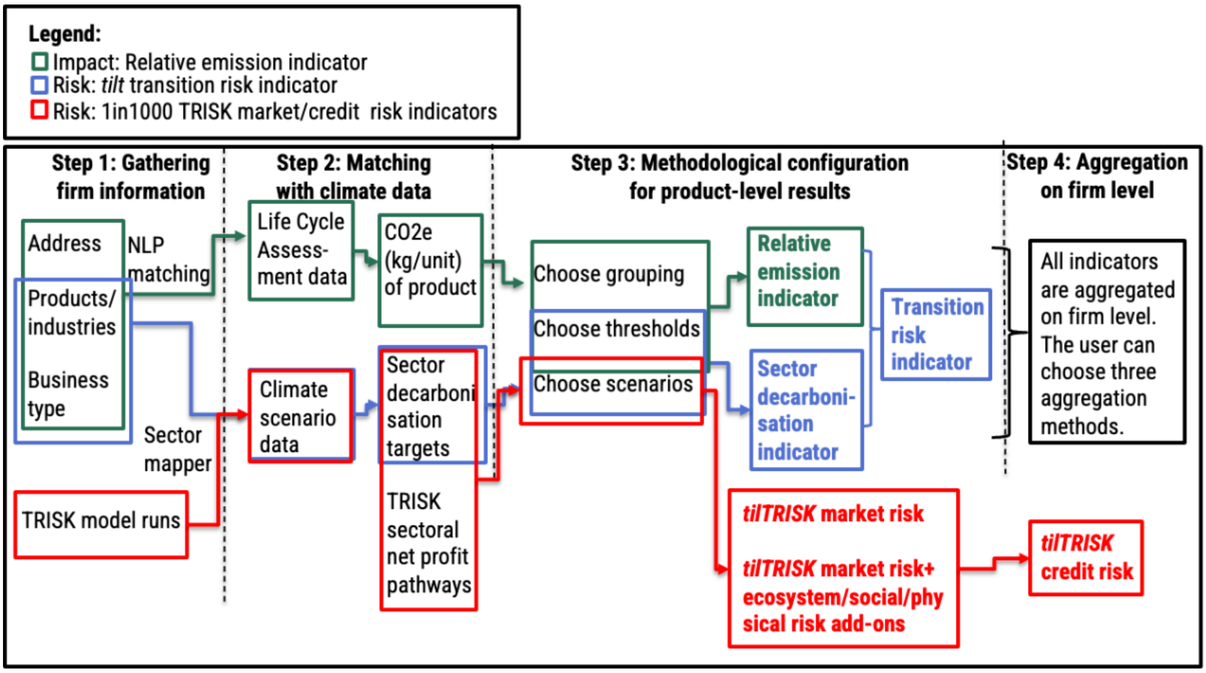

Figure 1: schematic representation of the methodological steps for the tilt and tilTRISK indicators

First, the **relative emission intensity indicator** for the impact perspective. The steps to creating the indicator are highlighted in green in Figure 1. The relative emission intensity indicator measures a product's emission intensity expressed in carbon dioxide equivalents (CO2e) per product unit (CO2e kg/unit) compared to the emission intensity of other products. The relative emission indicator is a number between 0 - the product with the lowest CO2e emission intensity in a specific group and 1 - the product with the highest CO2e emission intensity in a specific group. To contextualise the relative emission indicator and make them easier to interpret for users, tilt categorisse the products relative emission indicator into a low, medium and high category. After deriving the indicator on product level, the product results are aggregated on firm level. The goal of the relative emissions intensity is to allow for cross-company comparisons and highlight where emissions reductions can have the greatest impact. This approach helps banks and policymakers identify firms or sectors that most urgently need to improve their emissions performance and guides targeted transition financing and policy support.

Second, the **transition risk indicator** for the risk perspective. The methodological steps for this indicator are highlighted in blue in Figure 1. While firms impact climate change via emitted CO_2e, the risk from climate change to the firm's capacity to produce and maintain profits is affected the interaction of climate **hazard, vulnerability, and exposure**[1], creating a source of climate transition risk.

Transition risks stem from financial, strategic, and operational challenges that firms face when adapting to a low-carbon economy. These risks are driven by changes in policy, technology, market preferences, and legal frameworks, all of which require firms to reduce their CO_2e emission intensity. For example, the EU's Green New Deal, targeting net-zero emissions by 2050, requires firms to adopt green technologies and reduce associated costs.

In the climate transition setting, the **hazard** is driven by policy goals (e.g., net-zero targets) requiring firms to cut emissions, which are represented in climate transition scenarios. Firms with higher CO_2e emission intensity face greater exposure to scenario policies such as carbon taxes, which raise costs per unit of emissions. While vulnerability—how ready a firm is to adapt—matters, it is challenging to measure without specific firm data on transition plans. Therefore, the *tilt* transition risk indicator focuses on hazard (sector decarbonization) and exposure (relative emissions), combining the sector decarbonization indicator with a firm's relative emission intensity. This produces a measure that captures a firm's transition risk in relation to others, highlighting where policy interventions and adaptation measures are most needed.

However, the transition risk from *tilt* does not fully capture the climate vulnerability component because it does consider firm-level operational climate adapation information such as whether a firm is making identifiable steps towards reducing its carbon footprint by investing in less carbon intensive technologies or implementing transition plans. The transition risk indicator is neither considering the firm's financial risk position and how it is impacted by the SME-firm-specific climate transition shock and adaptation story. Neither the *tilt* transition risk indicator considers wider adaptive capacity of the considered sectors and their climate positive technological opportunities.

[1] IPPC, 2014, p.36

The new set of *tilTRISK* indicators are designed to offer a way of bridging these methodological gaps. *tilTRISK* is the result of combining SME data points from the *tilt* database with the detailed and flexible transition risk estimates from the TRISK model which is granular climate transition risk stress model designed to be highly flexible in terms of application use cases and methodologies. The first step is to calculate the vulnerability of production capacity and profits for 45,000 large firms globally in climate-critical sectors—i.e., firms of different order but in the same sectors covered by *tilt* and the climate scenarios *tilt* uses. TRISK model runs estimate how these large firms are to be impacted under a variety of climate transition scenarios that assume a range of CO2e carbon emission pathways. These CO2e pathways are translated into production volumes for each production process categorized at technology level and from these it then becomes possible to derive sector-level net profit pathways for the same industries, regions and scenarios that appear in the tilt database, assuming that shock factors "spill over" from large firms to tilt's SME population in those corresponding regions and sectors. In doing so, TRISK produces a set of *tilTRISK* indicators that capture this often-missing vulnerability component of climate transition risk for SMEs in tilt.

3. tilTRISK methodology

Introduction

tilTRISK is a transparent and scalable climate transition financial risk methodology and a set of indicators covering over 200,000 European SMEs, resulting of combining SME data points from the *tilt* database with the detailed and flexible transition risk estimates from the TRISK model. These indicators can be calculated using the *tilTRISK* online SME portfolio assessment tool, which is integrated into the 1in1000 Climate Risk Intelligence Solutions Platform (CRISPY). The objective of the tilTRISK is to:

1) Assess small and medium enterprises (SMEs) on their climate transition vulnerability; and
2) Empower investors and financial institutions with a measute of the climate-related financial risk on SMEs' equity and the credit risk on loans issued to them.

tilTRISK builds on *tilt* by incorporating an enhanced climate vulnerability element into the estimation of the ***tilTRISK* market risk** SME valuation shock—indicating how much an SME firm's market value (or Net Present Value, NPV) may decline in response to a sudden climate transition. This indicator is then further developed for a measure of ***tilTRISK* credit risk** impacts using a structural Probability of Default (PD) model, which estimates the likelihood that a loan to a given SME will default. As these TRISK-derived indicators quantify financial risk for SMEs, they readily align with the needs of banks and other financial institutions, allowing for aggregation into portfolio-level risk metrics. A bank can therefore use these indicators to evaluate how a chosen set of climate scenarios could affect the financial risk of its SME portfolio, bridging the gap between tilt's relative emissions analysis and a more robust, financially oriented measure of transition risk than was originally offered by *tilt*.

Motivation

1in1000 designed the *tilTRISK* with the motivation of bringing climate financial risk considerations into SME portfolios. This approach supports the double materiality perspective in finance and lending decisions, expanding the assessment beyond large listed corporate portfolios to include SMEs. By linking SME climate indicators with a radically transparent, granular and flexible climate stress testing analysis, financial institutions gain deeper insights into transition risks and their portfolios' environmental footprints, they can use the *tilTRISK* indicators to quantifiably calculate climate-related risks in SME portfolios, understand how to develop data-driven climate strategies to transition their SME portfolios for a net zero future.

The key added value of the *tilTRISK* indicator is its integrability with traditional financial risk magement metrics such as the discounted cash flow (DCF) model for corporate Net Present Value (NPV) and structural models like the Merton model for probability of default (PD). This enables a more seamless expansion of climate financial risk management to the SMEs portfolios of investors and banks. First, it ensures that climate transition related factors (e.g., policy changes in climate scenarios) are translated into tangible impacts on cash flows and balance-sheet stability. Second, embedding these risks into conventional credit and valuation frameworks helps maintain consistency and comparability across a firm's entire risk management practice, preventing climate risk from being treated as a stand-alone or "nice-to-have" metric. Third, aligning climate considerations with established financial models fosters internal buy-in and clarity among different stakeholders—finance teams, senior management, and regulators—making it easier to integrate climate risk into capital allocation, pricing decisions, and stress tests. Finally, this approach addresses evolving regulatory and market expectations, as supervisors increasingly require comprehensive quantitative assessments of how climate risks affect financial risks and the long-term business model.

Data

TRISK data

The TRISK model utilises several data inputs to develop a unique climate stress test measure of credit and market risk for each individual large listed company in the dataset. The first type of data inputs is a highly granular production asset data for approximately 15 thousand assets including information on production activity, such as business unit production plans, and corporate ownership structure in the power generation and steel prodiuction industries. The key aspect of the asset-based production data is that it is forward-looking which means that the data cover both on the company's production capacity today and the production plans going forward by 5 years. This allows asset-specific assessments on market risk and credit risk based on asset-level production shocks, and differences in carbon pricing policies between countries based on the asset location. The assets in this analysis are a sample of the dataset of production assets that can be developed internally using open-source sources of data such as the Global Energy Monitor, Spatial Finance Initiative and Climate Trace. Different data points on each asset such as asset type, production capacity, emissions profile and location are collected from these databases, processed and cleaned using R packages developed at Theia Finance Labs to remove inconsistencies. The data points are then cross-linked and validated across the three sources to create a comprehensive and consistent set of assets. The second type of data inputs are the company-level information on company finances and financial risk profiles sourced from Refinitiv Eikon. This includes data on market capitalisation, asset volatility, structural leverage ratio, and net profit margin. The financial data is available only for publicly listed companies and for companies that are not publicly listed and tracked on Refinitiv Eikon. The missing data entries are completed using average values of those variables of companies in the same sector and country. The third type of data inputs are the climate scenarios which project the set of climate-adjusted economic parameters includes decarbonization and sectoral production pathways (across regions), unit cost projections and carbon tax pathways. We will elaborate on how climate scenarios are used in the dedicated climate scenario section below.

tilt data

tilt creates company indicators using internally sourced information on business type, location, and products. *tilt* gather this information from europages, operated by Visable GmbH. Europages is an international B2B platform with around 2.6 million companies from Europe, where firms self-report the required information. *tilt* evaluated various data sources, including Kompass, LinkedIn Business, Bold Data, Orbis by Bureau van Dijk, Open Corporates, and trade registries like the Dutch Kamer van Koophandel (KVK). After comparing coverage, benefits, limitations, costs, and data collection processes, europages was chosen for its comprehensive, free access and product-level data. The europages data covers firms in Austria, Germany, France, the Netherlands, and Spain. In total, the dataset includes approximately 280,000 firms across these countries with 31,383 products. tilt collects data via web scraping using an R package while ensuring responsible behaviour and limiting use to research purposes, not commercial use. For the relative emission indicator, tilt uses ecoinvent. Ecoinvent offers over 20,000 life cycle inventory (LCI) datasets across various sectors, including energy, construction, chemicals, and more. The database represents average production conditions in specific geographical locations, rather than company-specific data.

Climate scenario data

Climate–economy scenarios project alternate trends of key variables affecting the economy and the financial system including production for key sectors, potential carbon tax prices, and projections on the evolution of technological change in power generation. According to the IPCC (2022)[2], a climate scenario is a "plausible description of how the future may develop" based on consistent assumptions, not a forecast.

The tilTRISK indicators use the same scenarios sources as the original tilt indicator to determine sector-level GHG reduction targets:

1) Inevitable Policy Response (IPR) 2022 Forecast Policy Scenario (FPS) and the 1.5°C Required Policy Scenario (1.5°C RPS) model policy pathways to limit global warming to 1.5°C by 2050. IPR polls country-level experts on the likelihood and timing of specific measures, such as incentives to reduce agricultural emissions. These aggregated insights then inform scenarios projecting future CO_2 trajectories.
2) World Energy Outlook (WEO) 2023: Provided by the International Energy Agency (IEA), WEO offers three scenarios—Stated Policy Scenario (STEPS), Announced Pledges Scenario (APS), and Net-Zero Emissions Scenario (NZE), the latter modeling a pathway to Net Zero by 2050.

The table notes key distinctions between the WEO and IPR scenarios for our analysis. Both scenario concentrate on similar regions, offering global aggregates and European data, though Europe is defined slightly differently. For consistency, we used the global aggregates. WEO features more sector detail—28 sector-subsector groupings, including granular energy and power breakdowns—yet omits land use. IPR covers 14 groupings, including land use but lacks the detailed energy focus. IPR provides annual GHG emission data, while WEO uses five-year increments; both extend to 2050, letting tilt derive indicators for 2030 and 2050.

[2] IPPC, 2014, p.36

Regional granularity of projected GHG Emissions	Sectoral granularity of projected GHG Emissions	Time intervals	Time period	Costs	Emissions Variable	Average global temperature target	Over-shoot	Source + Documentation	Updates
Inevitable Policy Response (IPR), 1.5°C RPS									
Western Europe (WEU); Global	14 sector-subsector combinations, including transport, construction, industry, power, energy, and Land Use	1 year	2021-2050	Free	CO2	1.5°C by 2050	low overshoot before 2050	IPR's "Supporting Key Documents" (Link)	Annually
World Energy Outlook (WEO), by International Energy Agency (IEA), NZE Scenario									
Free dataset: Global Extended dataset: EU	28 sector-subsector combinations, including transport, construction, industry, power, energy.	5 year	2010-2050	Free / Extended: 640€ per user	CO2	1.4°C by 2100 (50% probability)	No overshoot before 2050	WEO 2023 Documentation and data (Link	Annually

Table 1: Summary of key parameters of the scenario providers.

Constructing the tilTRISK indicators

TRISK model runs

The TRISK model runs are used to determine sector-level corporate climate transition net profit pathways. Similarly to *tilt*, TRISK performs the calculations for each available climate scenario. Although it offers in principle a wider range of scenarios, for the purpose of the tilTRISK indicator we focus on two scenarios, one from IPR and and one from IEA WEO.

For each scenario run, there are several other model parameters that need to be specified listed in the table below – for more information on TRISK model parameters please consult the model source code and documentation on GitHub[3]. The TRISK model parameter settings that we used for tilTRISK are listed in Table 1:

Setting		Model Run #1	Model Run #2
Scenario Provider	Organisation that developed the climate scenario	IEA WEO	IPR
Baseline Scenario	The scenario provider's pathway indicating 'business-as-usual' climate policy, that is based on current policy setting with no or limited aditional action	Announced Policy Scenario	IPR Baseline
Target Scenario	The scenario provider's pathway indicating a 'Paris-Agreement-aligned' scenario of ambitious climate action	WEO SDS	IPR FPS
Shock year	The year in which the TRISK transition policy shock occurs, inducing a migration in corporate production trajectory from baseline to target	2030	2030
Discount Rate	The discount rate applied in the internal discounted cash flow model (DCF),	7%	7%

[3] To visit the model code repository: https://github.com/Theia-Finance-Labs/trisk.analysis
The manual can be found here: https://theia-finance-labs.github.io/trisk.analysis/

	fixed and consistent for all corporates		
Growth Rate	The long term real economic growth rate, used for calculating the terminal value of the DCF	3%	3%
Risk free rate	The long term interest rate of risk free assets used in the credit risk model	3%	3%
Region	Geographical focus of the scenario pathway	Europe	Global
Carbon Tax	Parameter indicating whether an additional carbon tax shock is applied	No	No

Table 2: TRISK model run parameters

The main difference between the model runs is the choice of baseline and target scenario and the region. For the IEA run, we have scenario data available for the region "Europe", which provides more granular and specific data for the European companies in tilt. For IPR, we do not have additional geographies incorporated in the model code, which is why we are running the model on a global region instead. For the remaining parameters, we keep default model settings and a 2030 shock year. More iterations and model runs with additional shock years could provide more distinct insights about the effect for the SMEs of an earlier or more delayed transition, which we might want to include in future updates. *tilt* also offers a categorization of the data based on country, in particular on France, Germany and Austria. To allow more accurate matching to related transition shock effects on the tilt companies, we further adjust our main model runs by including an filtering of the underlying asset-based data. The asset-based data for TRISK can be modified to only include companies that are operating in specific countries. We can apply these regional filters to get a more precise estimation of the potential transition risk shock for an average company operating in those regions. In essence, this means that we rerun the two highlighted model runs three times, with each having adjusted country-based production data. The matched outputs are based on average PD estimates, as well as the rate of change of the NPV, calculated based on the aggregated profit data for the underlying companies in the TRISK dataset.

Data matching and coverage

In the matching of data between tilt and TRISK and development of an automated mechanism, we use two pieces of information: sector classification and country geography. The matching mechanism relies on the definitions of the sector and subsector and the country geography columns as proposed by *tilt* and is set up to undergo two steps:

1) First, we match the sectoral and subsectoral categories between tilt and TRISK. *tilt* data categorizes each firm entry as belonging into a *tilt sector* and *tilt subsector* [4], while TRISK categorizes firms similarly in TRISK sectors that correspond to the macroeconic sectors the firm operate in with a single physical output (i.e Power and KWh) and TRISK business units which denominate the subsector technologies used to produce the sectoral output (i.e. Renewables technology power in KWh). The sectoral and business unit for a small number of sectors directly correspond between *tilt* and TRISK which significantly improves the matching process. For the first version of the *tiltrisk* we chose to match on two sectors and subsectors that have direct correspondece as outlined in the Table 3 below.

tilt Sector	*tilt* subsector	TRISK Sector	TRISK business_unit
Power	Total Power	Power	Total power
Energy	Gas Energy	Oil&Gas	Gas
Energy	Oil Energy	Oil&Gas	Oil

Table 3: tilt and TRISK current sector coverage

[4] For more information how *tilt* defines sectors and subsectors please consult *tilt* methodology in Schönauer, A., Trompke, T., & et al. (2024)

2) Second, we match the sector-defined firms using another layer of distiction and that is their country location and the nearest TRISK geographical match. In the first version of *tiltrisk* we use data from firms in Austria, France and Germany. Based on the sector and subsector firms in those countries operate in, they are matched to nearest scenario geographies available by IEA WEO and IPR scenarios. If there is no country level geography available, the matching mechanism automotically steps one geographical layer up, i.e.to EU or Global geography or whichever lowest corresponding granularity is available.

With this, we can match the two TRISK model runs to 13 355 different companies operating in two sectors and three subsectors in *tilt*. The resulting dataframe tracks each company on a separate row with columns identifying the firm's sector in tilt and TRISK, the model run identifier and the tilTRISK estimates like can be seen in the picture below. Additionally to sector and subsector classification, each firm is identified by their 'main_activity' which firm's main activity in the whole economy value chain, i.e. is the firm a distributor, whosaler, retailer etc.

company_name	country	main_activit	clustered	activity_uuid	activity_name	isic_4digit	tilt_sector	tilt_subsecto	ald_sector	ald_business	run_id	Change_NPV	Change_NPV	Change_NPV	Change_NPV	scenario_ge	baseline_sce	shock_scena
Firm A	germany	wholesaler	electricity	c9407332-80	market for electricity, medium voltage	3510	power	total power	Power	Total Power	d24c3a42-23	0.05798045	0.03133397	-0.0777983	-0.2170566	Europe	WEO2021_A	WEO2021_SD
Firm A	germany	wholesaler	electricity	c9407332-80	market for electricity, medium voltage	3510	power	total power	Power	Total Power	d24c3a42-23	0.05798045	0.03133397	-0.0777983	-0.2170566	Europe	WEO2021_A	WEO2021_SD
Firm A	germany	wholesaler	electricity	c9407332-80	market for electricity, medium voltage	3510	power	total power	Power	Total Power	d24c3a42-23	0.05798045	0.03133397	-0.0777983	-0.2170566	Europe	WEO2021_A	WEO2021_SD
Firm A	germany	wholesaler	electricity	c9407332-80	market for electricity, medium voltage	3510	power	total power	Power	Total Power	d24c3a42-23	0.05798045	0.03133397	-0.0777983	-0.2170566	Europe	WEO2021_A	WEO2021_SD
Firm A	germany	wholesaler	electricity	c9407332-80	market for electricity, medium voltage	3510	power	total power	Power	Total Power	d24c3a42-23	0.05798045	0.03133397	-0.0777983	-0.2170566	Europe	WEO2021_A	WEO2021_SD
Firm A	germany	wholesaler	electricity	c9407332-80	market for electricity, medium voltage	3510	power	total power	Power	Total Power	32a7d72b-48	0.10030244	0.07552452	-0.025955	-0.155448	Global	IPR2023_bas	IPR2023_FPS
Firm A	germany	wholesaler	electricity	c9407332-80	market for electricity, medium voltage	3510	power	total power	Power	Total Power	32a7d72b-48	0.10030244	0.07552452	-0.025955	-0.155448	Global	IPR2023_bas	IPR2023_FPS
Firm A	germany	wholesaler	electricity	c9407332-80	market for electricity, medium voltage	3510	power	total power	Power	Total Power	32a7d72b-48	0.10030244	0.07552452	-0.025955	-0.155448	Global	IPR2023_bas	IPR2023_FPS
Firm A	germany	wholesaler	electricity	c9407332-80	market for electricity, medium voltage	3510	power	total power	Power	Total Power	32a7d72b-48	0.10030244	0.07552452	-0.025955	-0.155448	Global	IPR2023_bas	IPR2023_FPS
Firm A	germany	wholesaler	electricity	c9407332-80	market for electricity, medium voltage	3510	power	total power	Power	Total Power	32a7d72b-48	0.10030244	0.07552452	-0.025955	-0.155448	Global	IPR2023_bas	IPR2023_FPS
Firm B	austria	distributor	gas	11fb8678-d8	market for natural gas, vented	610	energy	oil energy	Oil&Gas	Oil	d24c3a42-23	-0.4316753	-0.4395503	-0.4718027	-0.5129585	Europe	WEO2021_A	WEO2021_SD
Firm B	austria	distributor	gas	11fb8678-d8	market for natural gas, vented	610	energy	oil energy	Oil&Gas	Oil	d24c3a42-23	-0.4316753	-0.4395503	-0.4718027	-0.5129585	Europe	WEO2021_A	WEO2021_SD
Firm B	austria	distributor	gas	11fb8678-d8	market for natural gas, vented	610	energy	oil energy	Oil&Gas	Oil	d24c3a42-23	-0.4316753	-0.4395503	-0.4718027	-0.5129585	Europe	WEO2021_A	WEO2021_SD
Firm B	austria	distributor	gas	11fb8678-d8	market for natural gas, vented	610	energy	oil energy	Oil&Gas	Oil	d24c3a42-23	-0.4316753	-0.4395503	-0.4718027	-0.5129585	Europe	WEO2021_A	WEO2021_SD
Firm B	austria	distributor	gas	11fb8678-d8	market for natural gas, vented	610	energy	oil energy	Oil&Gas	Oil	d24c3a42-23	-0.4316753	-0.4395503	-0.4718027	-0.5129585	Europe	WEO2021_A	WEO2021_SD
Firm B	austria	distributor	gas	11fb8678-d8	market for natural gas, vented	610	energy	oil energy	Oil&Gas	Oil	32a7d72b-48	-0.6331174	-0.6354094	-0.6447963	-0.6567744	Global	IPR2023_bas	IPR2023_FPS
Firm B	austria	distributor	gas	11fb8678-d8	market for natural gas, vented	610	energy	oil energy	Oil&Gas	Oil	32a7d72b-48	-0.6331174	-0.6354094	-0.6447963	-0.6567744	Global	IPR2023_bas	IPR2023_FPS
Firm B	austria	distributor	gas	11fb8678-d8	market for natural gas, vented	610	energy	oil energy	Oil&Gas	Oil	32a7d72b-48	-0.6331174	-0.6354094	-0.6447963	-0.6567744	Global	IPR2023_bas	IPR2023_FPS
Firm B	austria	distributor	gas	11fb8678-d8	market for natural gas, vented	610	energy	oil energy	Oil&Gas	Oil	32a7d72b-48	-0.6331174	-0.6354094	-0.6447963	-0.6567744	Global	IPR2023_bas	IPR2023_FPS
Firm B	austria	distributor	gas	11fb8678-d8	market for natural gas, vented	610	energy	oil energy	Oil&Gas	Oil	32a7d72b-48	-0.6331174	-0.6354094	-0.6447963	-0.6567744	Global	IPR2023_bas	IPR2023_FPS
Firm C	austria	distributor	oil	4438999c-70	market for petroleum	4661	energy	gas energy	Oil&Gas	Gas	d24c3a42-23	-0.75736	-0.7596653	-0.7691071	-0.7811553	Europe	WEO2021_A	WEO2021_SD
Firm C	austria	distributor	oil	4438999c-70	market for petroleum	4661	energy	gas energy	Oil&Gas	Gas	d24c3a42-23	-0.75736	-0.7596653	-0.7691071	-0.7811553	Europe	WEO2021_A	WEO2021_SD
Firm C	austria	distributor	oil	4438999c-70	market for petroleum	4661	energy	gas energy	Oil&Gas	Gas	d24c3a42-23	-0.75736	-0.7596653	-0.7691071	-0.7811553	Europe	WEO2021_A	WEO2021_SD
Firm C	austria	distributor	oil	4438999c-70	market for petroleum	4661	energy	gas energy	Oil&Gas	Gas	d24c3a42-23	-0.75736	-0.7596653	-0.7691071	-0.7811553	Europe	WEO2021_A	WEO2021_SD
Firm C	austria	distributor	oil	4438999c-70	market for petroleum	4661	energy	gas energy	Oil&Gas	Gas	d24c3a42-23	-0.75736	-0.7596653	-0.7691071	-0.7811553	Europe	WEO2021_A	WEO2021_SD
Firm C	austria	distributor	oil	4438999c-70	market for petroleum	4661	energy	gas energy	Oil&Gas	Gas	32a7d72b-48	-0.6507402	-0.6527581	-0.6610227	-0.6715687	Global	IPR2023_bas	IPR2023_FPS
Firm C	austria	distributor	oil	4438999c-70	market for petroleum	4661	energy	gas energy	Oil&Gas	Gas	32a7d72b-48	-0.6507402	-0.6527581	-0.6610227	-0.6715687	Global	IPR2023_bas	IPR2023_FPS
Firm C	austria	distributor	oil	4438999c-70	market for petroleum	4661	energy	gas energy	Oil&Gas	Gas	32a7d72b-48	-0.6507402	-0.6527581	-0.6610227	-0.6715687	Global	IPR2023_bas	IPR2023_FPS
Firm C	austria	distributor	oil	4438999c-70	market for petroleum	4661	energy	gas energy	Oil&Gas	Gas	32a7d72b-48	-0.6507402	-0.6527581	-0.6610227	-0.6715687	Global	IPR2023_bas	IPR2023_FPS
Firm C	austria	distributor	oil	4438999c-70	market for petroleum	4661	energy	gas energy	Oil&Gas	Gas	32a7d72b-48	-0.6507402	-0.6527581	-0.6610227	-0.6715687	Global	IPR2023_bas	IPR2023_FPS

Table 4: example tilTRISK matching output table

In terms of coverage, it is worth noting that this is a reduced share of the original *tilt* dataset covering the approximately 280 000 firms. The reason for this is fact that we chose two tilt sectors to implement in the initial version of the tiltrisk database. As we update the tiltrisk database to cover more sectors this number should grow significantly.

Indicators

tiltrisk market risk

The tilTRISK market risk indicator estimates how much market equity value a company may lose under a disruptive late-and-sudden climate transition[5]. TRISK evaluates this risk for large corporations by translating production shocks into profit projections: for a given large corporate firm *i* and year *t*, net profit is derived by multiplying the production volume by the unit price and unit cost of the corresponding production technology *s*

$$Net\ Profit_{i,t} = production\ volumei_{i,t,s} \times \left(unit\ price_{t,s} - (unit\ cost_{t,s} + carbon\ tax_{t,s})\right)$$

The net profits are consequenlty discounted to assess changes in corporate equity valuations. Then we assume that future profits are to be distributed as dividend payouts to equity investors. Consequently, the NPV of a company equity is represented as the cumulative discounted sum of future net profits. For a given firm *i* and year *t*, using the cost of equity as the discount rate, the discounted net profit is calculated as:

$$Discounted\ net\ profit_{i,t} = \frac{\text{Net profit}_{i,t}}{(1 + discount\ rate)^t}$$

The NPV of net profits for a given scenario is obtained by summing all future discounted net profits

$$Net\ Present\ Value_{i,t} = \sum_{shock\_year}^{2050} Div_{ratio} \times Discounted\ net\ profit_{i,t}$$

The total Net Present Value for all firms in subsector (or business unit) *b* is obtained by summing the NPV of each firm with its market share within the subsector *b* like so

[5] For a comprehensive description of the climate scenario mechanics in TRISK please refer to the Appendix

$$Net\ Present\ Value_b = \sum_k^j Net\ Present\ Value_i \times market\_share_{i,b}$$

The subsector NPVs are then matched to the *tilt* companies. The final tilTRISK market risk indicator, the equity value change due to transition shock is then the percentage difference between NPV baseline and NPV shock. This metric thus constitutes a measure of company market risk because of transition shock:

$$Equity\ value\ change = NPV\ baseline — NPV\ shock$$

By summing these individual large-firm losses into a sector/country-level total—and given that large firms typically dominate the sector's production profile—this figure becomes a proxy for any firm in that sector and region. For SMEs, the same technology and supply chain structures typically apply, meaning they can face similar cost pressures, carbon price dynamics, and policy shifts as the large firms. Additionally, smaller companies often rely on these larger entities for inputs, markets, or logistical support, creating production-process spillovers that amplify the impact of the same transition risks. Consequently, the aggregated NPV impacts calculated for large firms serve as a statistically and economically meaningful reflection of the transition risk that SMEs face in the same sector and region.

tiltrisk market risk with ecosystem, social, and physical risk add-ons

A key challenge in interpreting climate transition risk outcomes is the limited scope often found in conventional climate risk analyses. Typically, these analyses rely on disruptive climate scenarios, such as the late-and-sudden transition scenario used in TRISK. However, several issues arise with this approach: the scenarios often represent a central estimate under a high-carbon future rather than more pessimistic outlooks of severe economic disruption; they rarely incorporate the additional effects of physical or social tipping points; they may understate risks at lower temperature thresholds as negligible; and they focus almost exclusively on direct climate impacts while overlooking potential social or ecosystem shocks.

To address these shortcomings, we designed this indicator to capture the potential financial losses for SMEs under a more comprehensive stress-test scenario—one that integrates climate tipping points alongside social and ecosystem risks. Our approach builds on the 1in1000-LIFE STRESS report, "How climate stress test may underestimate financial losses from physical climate risks" (2024), which aggregates academic research on macroeconomic effects of climate change (both with and without tipping points), ecosystem service loss, and social tipping points. We use this information to develop "add-on" climate value impact pathways extending to 2050, reflecting how both transition risk and these additional factors manifest over time. These pathways are then integrated into the TRISK multi-period discounted cash flow model, enabling simulations of valuation losses or diminished returns under different scenarios and producing tilTRISK market risk estimates with ecosystem, social, and physical risk add-ons. The following sections outline the methodology for each category of add-on risk.

1) *Ecosystem Tipping Points*

For ecosystem costs, we are relying on ecosystem cost approximations from the WWF and World Bank, which sum up to an ecosystem cost, or 'ecofactor' of 2.93%. We assume that these are the estimated reduction in profits a company might face at the stress test end year. [6] We further assume that the cost for ecosystems is linearly increasing starting from the shock year of 2030 and growing then until the total costs calculated for the final year. We then subtract these costs from the aggregated net present values calculated for each business unit and model run, which contain the same profits that also informed the original relative change in NPV calculated original from the TRISK model framework.

The following is a breakdown of the analytical steps, using an example of the WEO run for Germany and the Oil sector:

1. Calculate the Ecosystem Costs:

[6] Original, these are costs on GDP level, which we translate now into firm specific shocks.

As a first step we calculate the ecosystem costs (EcoCosts), by using the previously mentioned ecofactor of 2.93% and the aggregated profits calculated in the IEA scenario for Oil in the year 2040

$$(1)\quad EcoCosts_{t=2040} = ecofactor * Profits_{IEA,Oil,t=2040}$$

2. Distributing the costs

We are assuming that the costs are increasing linearly each year starting from the shock year. To calculate the annual additions, we divide the EcoCosts by the number of years we have after the shock year, which in this case for IEA are 11. The Eco Cost Adjustments reflect then how much the additional costs accumulate to for each year after the shock year.

$$(2)\quad Eco\ Additions = \frac{EcoCosts}{(End\ Year - (Shock\ Year - 1)}$$

$$(3)\quad Eco\ Cost\ Adjustments_t = Eco\ Additions * (t - (Shock\ Year - 1))$$

3. Adjusting Profits

We then adjust the Shock Profits calculated from Trisk by adding the Eco Cost Adjustments for each year.

$$(4)\quad Adjusted\ Profits_{IEA,Oil,t} = Profits_{IEA,Oil,t} + Eco\ Cost\ Adjustments_t$$

4. Calculating NPV and relative change

Finally, we calculate the NPV of the TRISK and tilTRISK subsector by discounting all aggregated profits and aggregating them. This aggregation will also include a Terminal Value calculated based on the final value of Adjusted Profits.

$$(5)\quad NPV_{eco} = \sum_{t=2030}^{T} \frac{Adjusted\ Profits_{IEA,Oil,t}}{(1+r)^{(t-t0)}}$$

By calculating the %-change in NPV from Baseline to Eco adjusted NPV, we can see the additional impact from introducing these costs.

$$\%Change\ NPV\ with\ ECO = \frac{NPV_{eco}}{NPV_{base}} - 1$$

(6)

In this case, the original Trisk shock was -43% and the introduction of ecosystem costs increased this shock to -44%.

2) Social Risk add-on

For social risk we use the same approach as highlighted above, with the distinction that we are assuming a -12% social risk cost factor, which relies on a study by de Groot et al (2022)[7]. Note that we are assuming a cumulative addition of the two mentioned cost factors, which means that we aggregate the effect of ecosystem costs and social risk costs, giving us a total cost factor of 14.93%. In the example mentioned above, this would entail an additional valuation risk of 4% compared to our original calculated tilTRISK shock.

Shock Type	NPV %-change
Original tilTRISK market risk shock	-43%
Ecosystem Cost add-on	-44%
Ecosystem and Social Costs add-on	-47%

Table 5: Example Results of Ecosystem and Social Risk Inclusion

3) Physical Risk add-on

Another step in th process is to add physical risk costs, especially those costs which get introduced through the introduction of climate tipping points. Similar to the Ecosystem and social risk costs, we are again referring to the LIFE STRESS 1in1000 report on "How climate stress test may underestimate financial losses from physical climate risks.". As highlighted in the report, the additional shock is extrapolated from Dietz et al (2021), who estimate the impact on the social cost of carbon through climate tipping points. As in the

[7] De Groot, Olaf, Carlos Bozzoli, Anousheh Alamir (2022) "The global economic burden of violent conflict". Journal of Peace Research. https://journals.sagepub.com/doi/full/10.1177/00223433211046823

report, we use the $ change in social cost of carbon to suggest the additional profit reduction in the end year using their central estimate and the tail 10% tail probabiltiy. In this case, this results in a prisk cost fator of 18%, which we apply on the last available observation of aggregted trisk shock profits for each business unit and country selection and for the two scenarios. We then follow the same process as highlighted in the case above. In our case example, this would lead to a -48% NPV change compared to the baseline. Note that this cost is not cumulatively added to the ecosytem and social costs highlighted in the previous section. In a cumulative approach, the additional shock on NPV could be drastically higher.

Shock Type	NPV % change
Original tilTRISK market risk shock shock	-43%
Ecosystem Costs add-on	-44%
Ecosystem and Social Costs add-on	-47%
Physical Risk add-on	-48%

Table 6: Total Shock Type and NPV effect overview

tiltrisk credit risk

Thw ***tilTRISK* credit risk indicator measures the** impact using a structural Probability of Default (PD) model, which estimates the likelihood that a loan to a given SME will default as a result of a disruptive late-and-sudden climate transition[8].

The tilTRISK market risk valuation shifts under the shock scenario are incorporated into a time-adjusted Merton model, which estimates PD by comparing a firm's asset value to its liabilities. The PD calculation follows the standard normal CDF approach, where higher asset volatility increases default risk.

[8] For a comprehensive description of the climate scenario mechanics in TRISK please refer to the Appendix

$$(7)\ PD_{i,t} = = \Phi\left(-\left(\frac{\log(\frac{V_0}{L}) + (r - \frac{\sigma^2}{2})t)}{\sigma\sqrt{t}}\right)\right)$$

4. Analysis of results

Having completed the process of generating tilTRISK indicators, we produce a comprehensive analysis of the distribution of climate impacts for the base tilTRISK market risk NPV change indicator and for the tilTRISK credit risk PD change indicator. Results for the 13 355 tracked firms are first generated for each combination of country geography and climate transition scenario. Figure 2 below depicts the distribution of tilTRISK NPV change for the IPR Forecast Policy Scenario 2023 aggregated by firm's 'main_activity'.

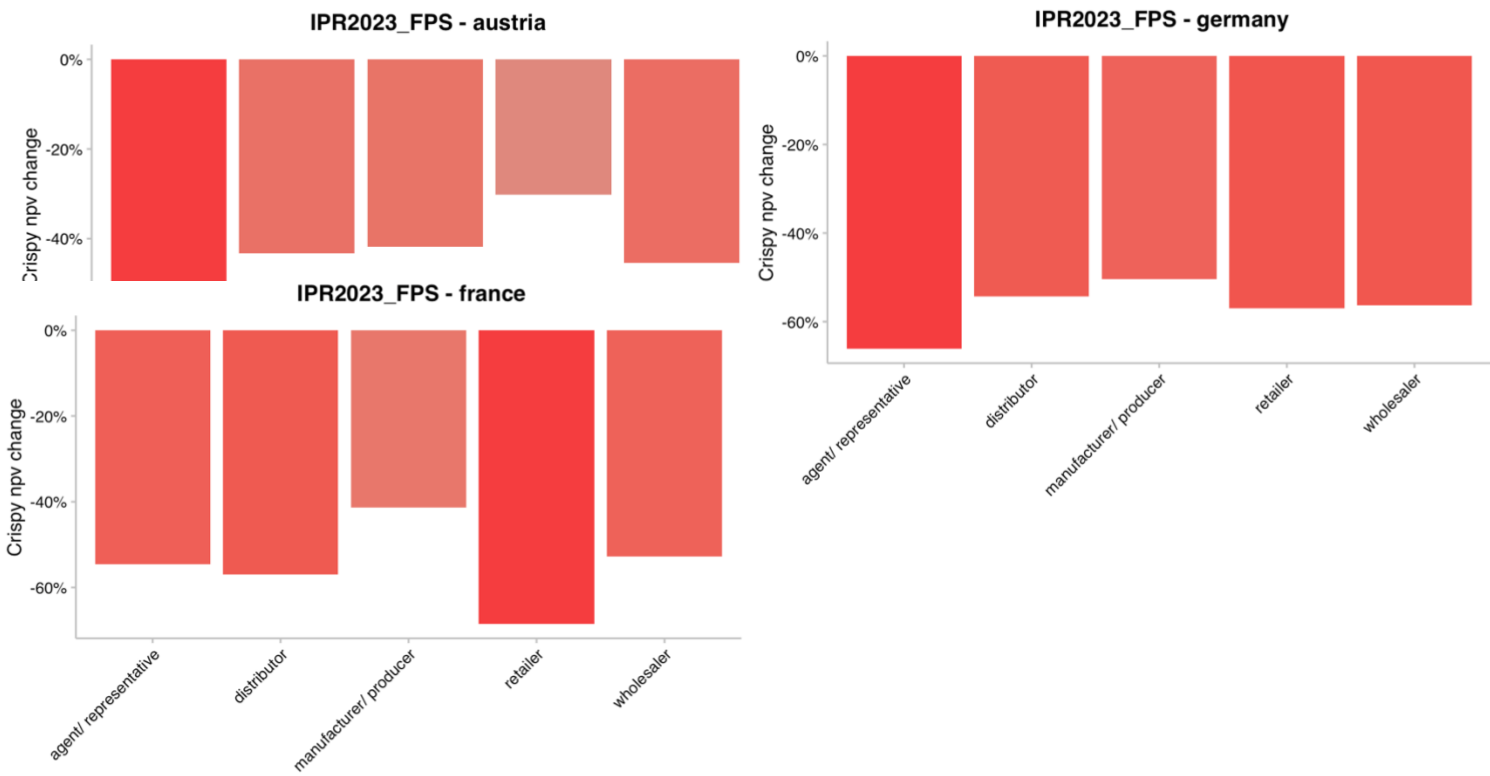

Figure 2: market risk NPV change per country and firm activity type for IPR FPS scenario

The results point to a clear finding: in the Energy and Power sectors all SME firms are to lose market value as a result of the transition risk shock with magnitude of between between 30% a 65% loss. The most significant loss are encountering firms in Germany, where the magnitude of the market risk indicator is between -50% and -63%. Next most impacted are firms from France, followed by Austria. In terms of firm main activity type, the results are more mixed. For the more impacted firms in Germany, it is the agent/representative activity that is undergoing most loss, similarly for Austria, while in France these firms are relatively less impacted – there the most impacted activity type are retailers. Generally, the results seem to hint that manufacturer/producer activity types are relatively less impacted than others but our understanding of why this is the case is somewhat obscured. The likely reason are reporting distributional differences on the country level, where, for example, firms in France in the carbon-intensive and more transition risk impacted Energy sector are much more likely to be reported as retailers than same firms in Germany.

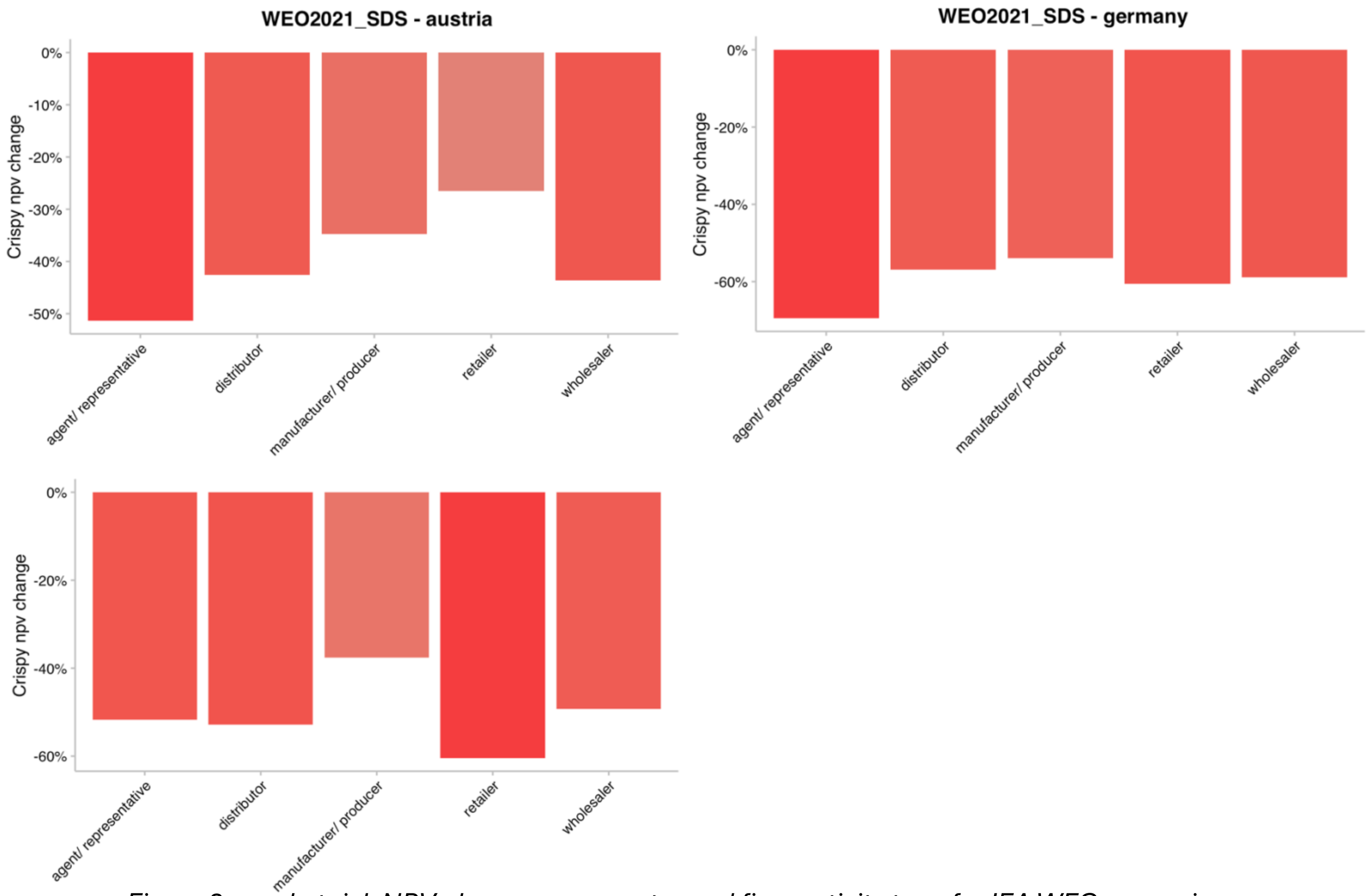

Figure 3: market risk NPV change per country and firm activity type for IEA WEO scenario

Results for the IEA WEO 2021 scenario paint a similar picture. The magnitude of the market risk indicator is generally higher for each country and firm activity type which is due to the higher carbon reduction ambition of the IEA WEO 2021 scenario versus the IPR FPS scenario. Again agent/representatives across all countries and retailers in France are the most impacted. Next, we aggregated the tilTRISK market risk NPV change as well as the credit risk PD change (more on PD change distribution below) results using a weighted average by firms main activity in Figures 4 and 5.

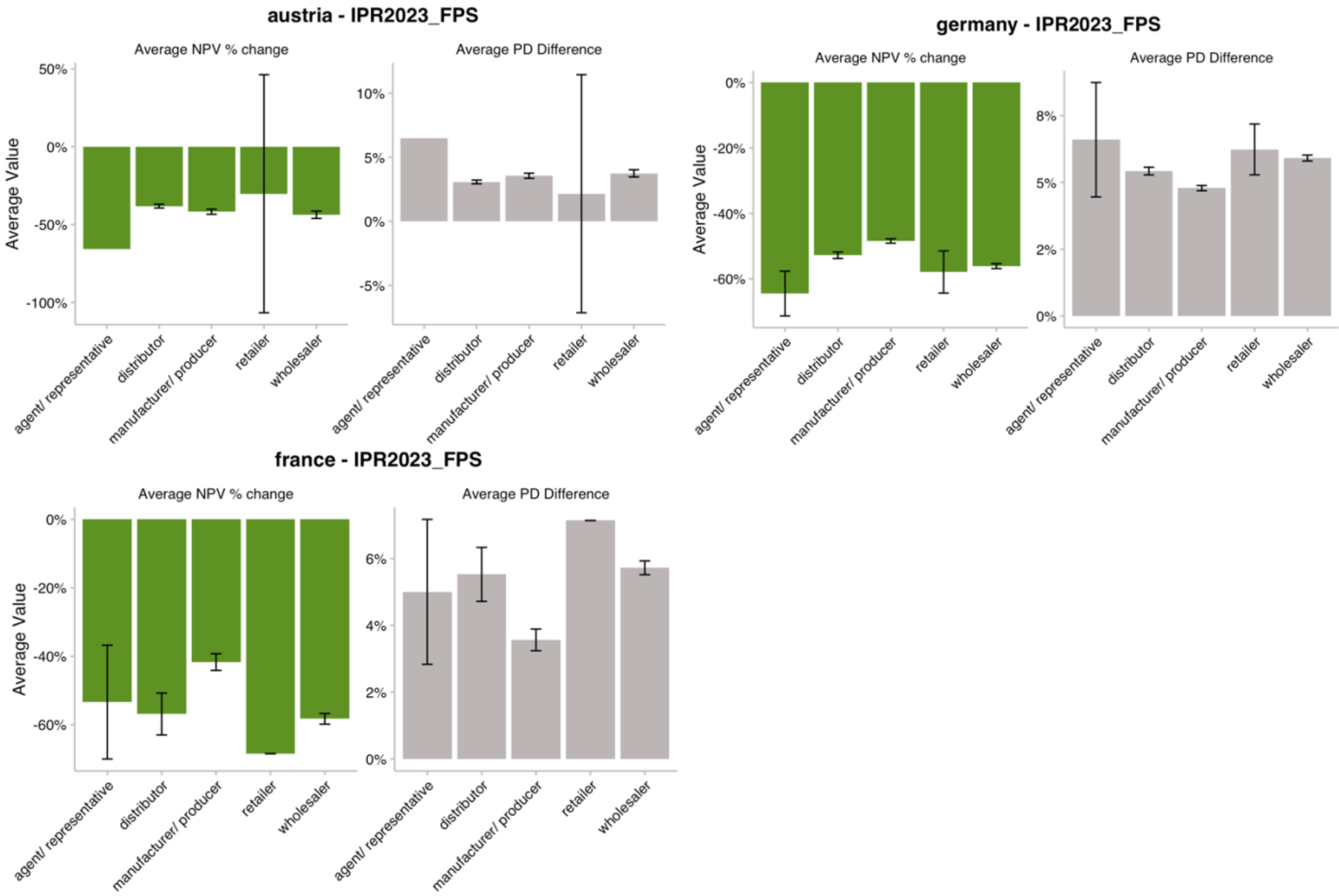

Figure 4: average NPV change, PD change and standard deviation range per country and firm activity type for IPR FPS scenario

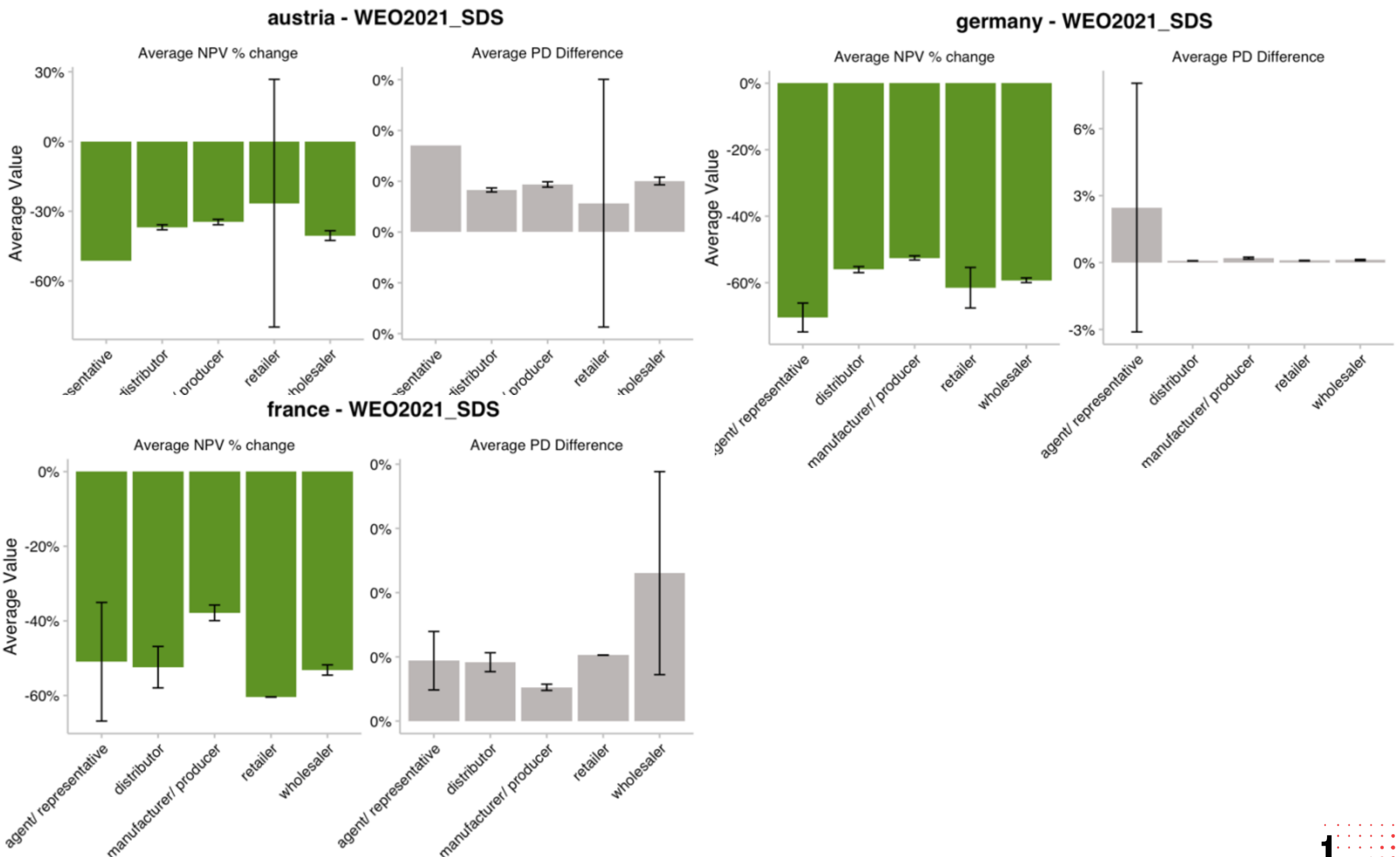

Figure 5: average NPV change, PD change and standard deviation ranges per country and firm activity type for IEA WEO scenario

Figures 4 and 5 illustrates that distribution of the NPV % change and the PD change for the IPR FPS scenario and for the IEA WEO 2021 SDS scenario when aggregated by weighted average on firm level generally follows the same results as in Figures 2 and 3 with total aggregation. Average PD change is for all firms positive, indicating an increase in credit risk of those firms as a results of climate transition shock. On the NPV change side, the widest range of distributed NPV change impacts appears for retailer firm types, especially in Austria. On the credit risk indicator the agent/representative firm activity type has the widest distribution of impacts.

The credit risk indicator is analyzed in the distribution of the PD changes is compared across firm activity types and loan maturity terms in Figures 6 and 7.

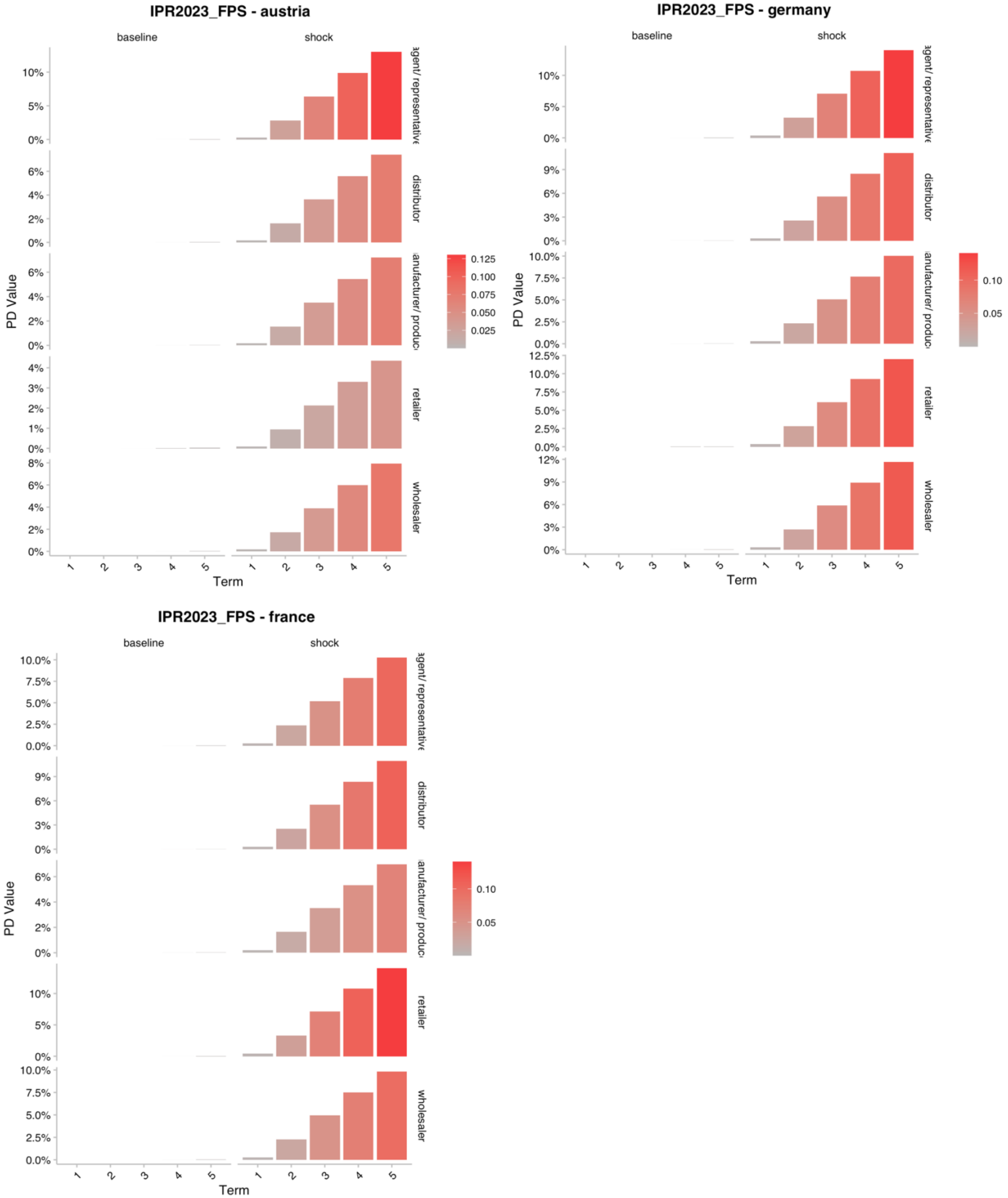

Figure 6: illustrates the probability of default (PD) changes across different firm activity types under IPR FPS scenario

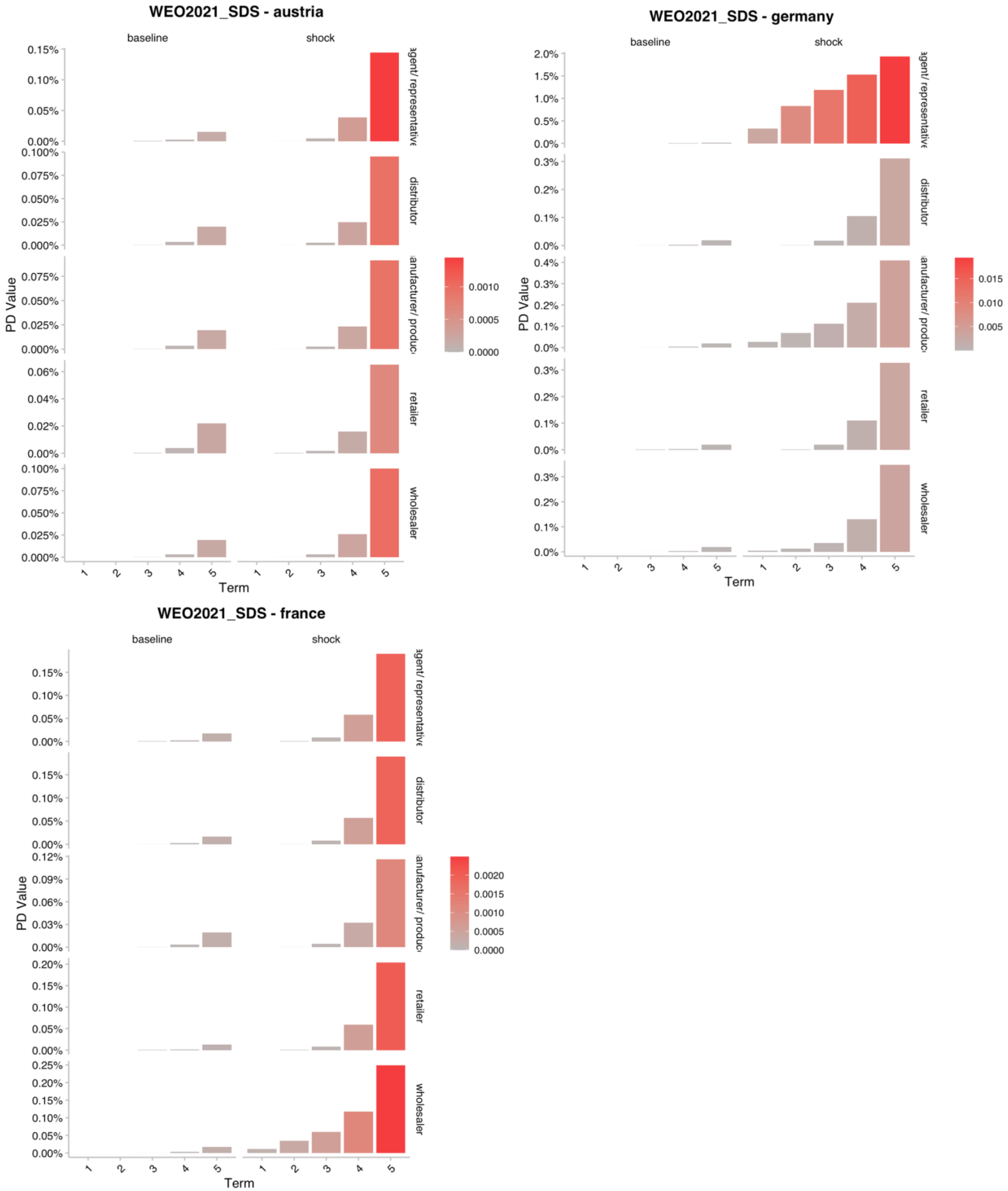

Figure 7: illustrates the probability of default (PD) changes across different firm activity types under IEA WEO scenario

For the IPR FPS scenario in Figure 6, results reveal a clear pattern: wholesale, manufacturer/producer and retailer firms experience the most substantial increases in credit risk (PD values) due to climate transition shocks. The most severe impacts for retailers are observed in Germany, where PD values under the shock scenario increase significantly above 12% PD change for the 5 year loan term. This aligns with expectations, as firms in these sectors are highly exposed to global supply chains and carbon-intensive operations, making them particularly vulnerable to transition risk shocks. Overall, firms in Austria exhibit more moderate increases in PD.

A further observation is the term sensitivity of credit risk. The PD values increase more substantially for longer-term maturities (4-6 years), indicating that climate transition shocks exert a continued influence on credit risk of longer maturities . In contrast, short-term credit risk remains relatively low, suggesting that immediate risks are less pronounced but could escalate as transition policies take effect.

Under the WEO2021 Sustainable Development Scenario (SDS), overall, the results of the PD change in Figure 7 display a generally significanly lower magnitude than for the IPR FPS scenario. The magnitude of PD increases in Germany significantly exceeds that of Austria and France, indicating a heightened vulnerability of SMEs in the German economy under a late and sudden transition scenario. Austrian firms show minimal PD shifts, while French firms experience moderate increases, particularly in wholesalers and manufacturers.

Next, we focus on analyzing the probability density plots for all SMEs aggregate for both chosen transition scenarios. The distribution for PD change of firms in Germany is almost always to the right of those for France and Austria, underlying the higher risk German SMEs are facing when undergoing a climate transition. France is close second and for some firm activity types such as distributor, the firms in France are riskier.

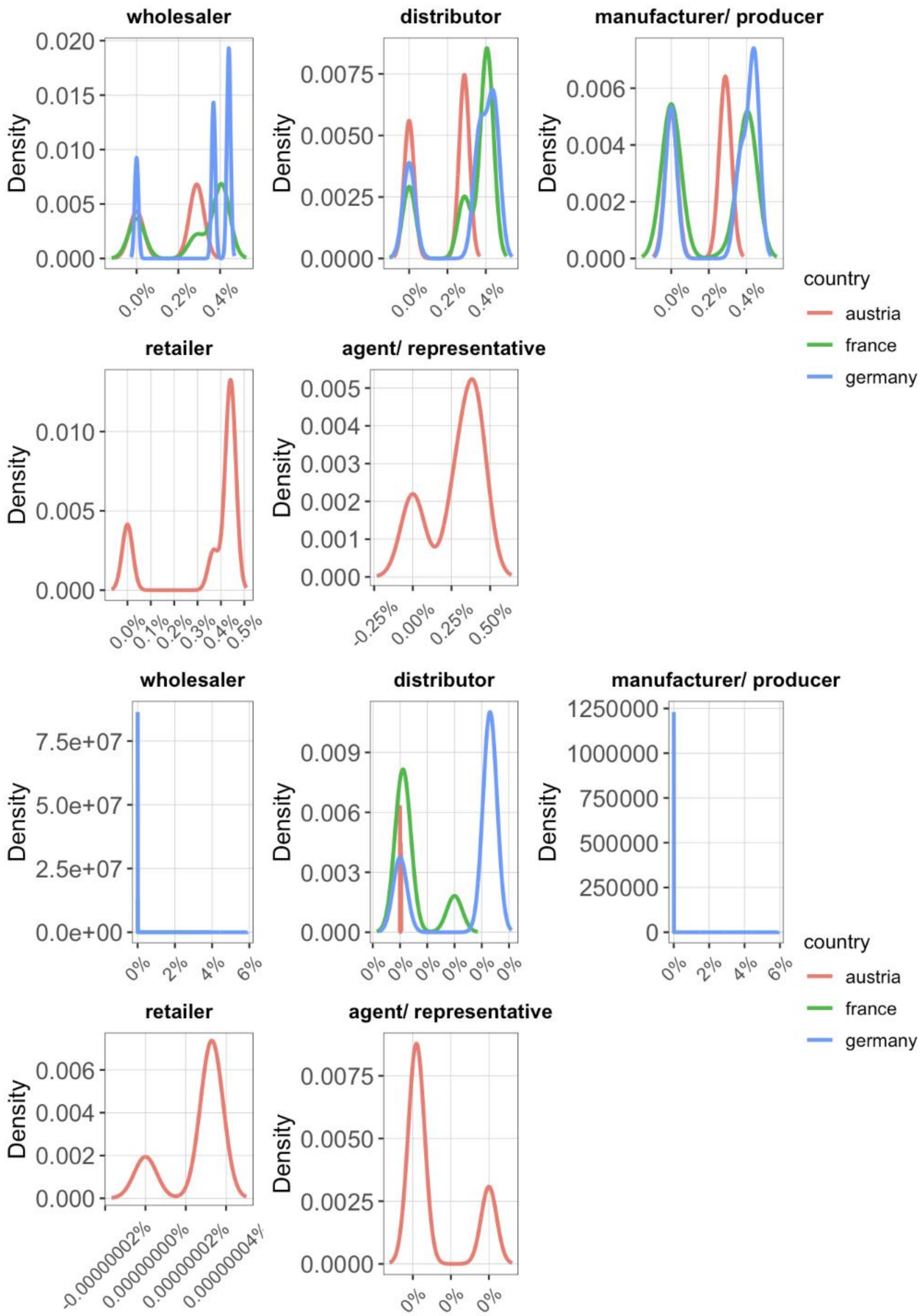

Figure 8: aggreagate probability of default (PD) changes across different firm activity for both scenarios

The difference in the distribution of tilTRISK market risk NPV change and the credit risk PD change indicator is best illustrated by comparing the probability densities across all firms for the two indicators. Figure 9 below shows that the IEA WEO scenario has larger negative NPV change (between -20 and -85%) which translates to higher positive PD change – and the distribution of observed PD changes is heavily concetrated aroung the +10% value. On the other hand, the impacts for IPR FPS are more muted, with NPV change between -40% and -60% and PD change.

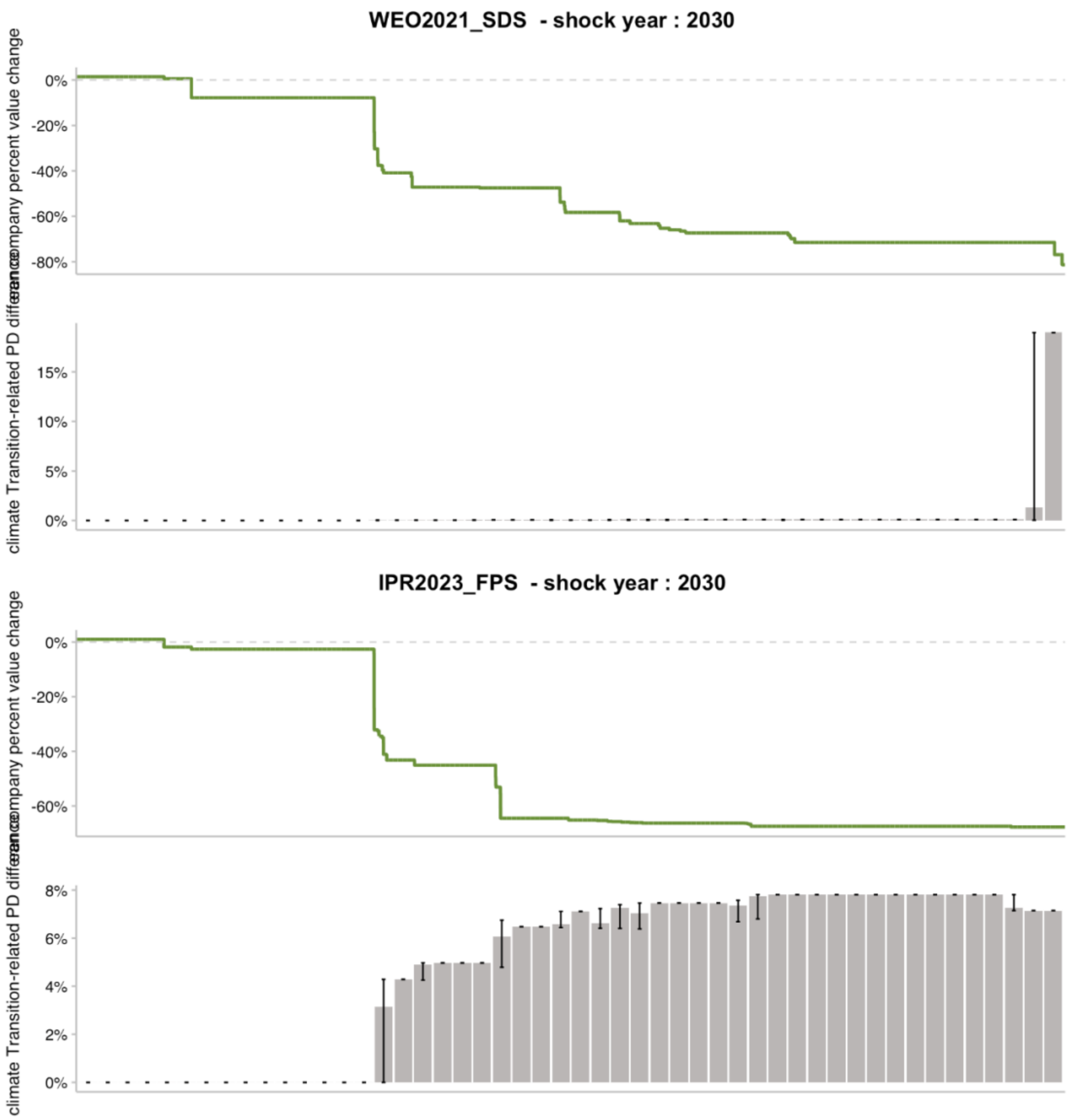

Figure 9: probability distribution of market risk NPV and credit risk PD change

5. Next steps in development

The tilTRISK indicators currently capture climate financial risk for small and medium-sized enterprises (SMEs) across several dimensions, namely transition, physical, ecosystem, and social risks. In the course of developing these indicators, we also considered a range of alternative methods and data sources for SME stress testing. Although we are presenting only the primary indicators at this stage, we view these other concepts as relevat next steps in refining and broadening the scope of tilTRISK. Future work will therefore investigate how incorporating new datasets, modeling assumptions, and analytical perspectives might further enhance the reliability and granularity of climate risk assessments for SMEs.

Adding scenarios

In the second iteration of tilTRISK, we plan to integrate multiple scenarios that build on or extend beyond the baseline and shock narratives found in the original tilt indicators. The goal is to offer a more nuanced corporate-level analysis that better captures the interplay between policy, technology, and market forces under different climate transition pathways. For instance, the baseline scenario in the IEA–WEO framework uses the Stated Policy Scenario (STEPS), while the Oxford–INET approach combines Oxford baseline assumptions with selected elements of IEA–STEPS. When applying the Inevitable Policy Response (IPR) scenarios such as IPR–NZE or IPR–B2DS, we often adapt IEA's STEPS as a reference baseline due to the absence of a dedicated baseline from IPR itself.

Additionally, the NGFS 2023 models (GCAM, REMIND, MESSAGEix) adopt Nationally Determined Contributions (NDC) as their baselines, reflecting the current policy pledges made by countries without major additional measures. Such diversity in scenario design allows us to examine how SME financial risk evolves in different policy landscapes—ranging from moderate decarbonization efforts in a "business-as-usual" world to more aggressive policy interventions that rapidly reshape energy and industrial systems.

Geographical spillover effects

An integral part of tilTRISK's next phase involves capturing the potential spillover effects of climate policies and sector disruptions at the local and regional levels. By mapping the geographic proximity of SMEs to large industrial sites in key climate-relevant sectors, we can approximate how changes in one business (for instance, the closure of a coal mine or the downsizing of a power plant) may ripple through surrounding communities. This approach draws on methods from spatial econometrics and value chain analysis, linking geolocation data with sector-specific economic structures to identify where local dependencies might amplify or mitigate transition risks.

Although we plan to begin with broader proxies—such as shared postal codes, upstream/downstream relationships, or logistical ties—subsequent iterations will seek to refine these measures with more granular data. By iteratively calibrating our dependence factors and updating them based on observed supply chain disruptions, the eventual aim is to produce spillover estimates that capture real-world complexities. This sensitivity-based framework will remain adjustable, allowing different financial institutions to customize parameters according to their own risk appetites, market exposures, or supervisory requirements.

Physical risk heatmap

Closely tied with the geographical perspective, further work on tilTRISK can also integrate physical climate hazards through the creation of a physical risk heatmap. This process involves obtaining vulnerability metrics—either derived from sector-specific databases or generalized climate impact studies—and overlaying SME locations onto hazard maps for events like floods, storms, and heat waves. With geolocation tools (e.g., Google's APIs), we can pinpoint the precise coordinates of each SME site and then model how each hazard scenario might affect local infrastructure and economic activity.

By layering these spatial datasets with climate projections for the short, medium, and long term, tilTRISK can produce scenario-specific estimates of how droughts, rising sea levels, or extreme weather might undermine a firm's operational capacity. In turn, these assessments become part of the broader stress test, complementing transition, ecosystem, and social risk indicators to reveal both immediate and cumulative vulnerabilities. Over time, as climate data and risk modeling techniques evolve, this component can be updated with more accurate hazard maps, sector-specific adaptations, or innovations in climate forecasting.

6. Conclusion

This report has introduced tilTRISK as a comprehensive tool for assessing climate-related financial risks among European SMEs, combining sector- and location-specific data from tilt with the detailed scenario modeling capabilities of TRISK. By integrating transition, physical, ecosystem, and social risk dimensions, tilTRISK offers a flexible framework that highlights how various industries and geographies respond to late-and-sudden climate policy changes. Analytical results presented—particularly the observed market value losses and increases in probabilities of default—indicate that certain sectors, such as Energy and Power, face substantial equity and credit risk exposures, with German SMEs frequently experiencing the largest shock effects. Meanwhile, even within individual countries, different business activities—retailers, wholesalers, manufacturers—display varying risk outcomes that underscore the importance of granular, firm-level indicators. Crucially, the findings suggest that longer loan maturities face a pronounced increase in default risk, reflecting a growing influence of transition pressures over time. This term sensitivity provides a valuable perspective for financial institutions in planning lending strategies and monitoring potential climate-induced credit deteriorations. Additionally, the comparisons between scenarios such as IPR FPS and WEO SDS show how divergent policy assumptions can produce markedly different risk intensities, reinforcing the need for multiple scenario analyses to capture the range of future uncertainties.

Although the indicators described here represent the primary outputs of tilTRISK's first phase, our work has underscored a number of promising avenues for future development. Scenario expansions in version 2 will incorporate models ranging from IEA–WEO STEPS to the NGFS 2023 frameworks, broadening the scope of possible policy and technology pathways. A new line of research will also emphasize geographic spillover effects, aiming to capture how closures or downsizing in major industrial sites reverberate across local supply chains. Furthermore, the integration of physical climate data through heatmaps will help uncover vulnerabilities to floods, heat waves, and other hazards, offering a more holistic assessment of climate exposure.

Taken together, these steps will push tilTRISK beyond its current focus on transition risk, enabling stakeholders to evaluate physical and systemic climate shocks with greater precision. By continuing to refine data inputs, modeling assumptions, and analytical techniques, we intend for tilTRISK to serve as a robust, transparent resource for financial institutions, investors, and policymakers. Ultimately, our objective is to foster a deeper understanding of how SMEs, which lie at the core of many economies, can navigate the challenges of climate transition and build resilience in the face of ever-evolving environmental and regulatory landscapes.

7. Appendix

TRISK methodology primer

TRISK is an asset-level, bottom-up microeconomic climate transition risk stress test (Baer et al., 2022). The model leverages the PACTA alignment approach (PACTA, 2020) to construct multiple scenarios of varying climate ambition at the company level through 2050, assessing the financial risks associated with late and abrupt transitions. Specifically, it propagates the climate-adjusted economic impacts of these scenarios to firms' asset values through a set of transmission channels, estimating potential changes in market valuation (market risk) and probabilities of default (credit risk). This methodology enables the measurement of transition risk at the levels of individual financial assets, counterparties, and aggregated portfolios.

Data

TRISK incorporates **three types** of data:

1) Scenario level data. The first data inputs are the climate–economy scenarios, which project the set of climate-adjusted economic parameters includes decarbonization and sectoral production pathways (across regions), unit cost projections and carbon tax pathways. The scenario parameters are exogenous and are sourced from multiple scenarios, including IEA WEO 2021, IPR FPS 2023, NGFS 2023, Oxford INET 2022.

2) Firm level production plans. The second type of input data includes granular, forward-looking production data at the appropriate level of granularity (e.g., asset, business unit, or company), provided by Asset Impact.

3) Firms' financial characteristics. The third type of input data consists of company-level financial information and risk profiles provided by Refinitiv Eikon. This includes metrics such as market capitalization, asset volatility, leverage ratio, and net profit margin. The data is available only for publicly listed companies. For non-publicly listed firms, missing entries are imputed using the sector and country averages of the respective variables.

Methodology

The model framework is composed of the **three methodological layers**.

The first layer of the TRISK framework involves constructing company-level climate financial scenario pathways. The model leverages the links between climate scenarios and company production plans to generate a range of late and sudden climate transition risk scenarios. These climate transition risk scenarios define how counterparties' production plans should align within decarbonization pathways to meet global temperature targets. The process begins by translating climate financial scenarios into technology-level decarbonization pathways following the PACTA market share attribution approaches (PACTA, 2020) to derive relative company climate targets. A company's decarbonization effort is assessed based on the alignment of its forward-looking production plans with these pathways and its market share within the sector. The methodology also allows for substituting firm-level projected production derived from scenario downscaling. Decarbonization efforts are distributed among companies in proportion to their market share within the sector—for example, a company with a 10% market share is responsible for 10% of the sector's decarbonization efforts. This framework implies that companies are expected to contribute to decarbonization in direct proportion to their size.

TRISK uses three types of decarbonization production pathways: (i) baseline, (ii) climate target, and (iii) climate transition shock. The *baseline* pathway represents a 'business-as-usual' scenario, reflecting no additional climate ambition beyond what is outlined in the company's forward-looking production plans. The *climate target* pathway depicts a sustainable production trajectory, assuming the company is already on a climate transition path both now and in the future, as defined by the input climate scenarios. The primary focus is the *climate transition shock* pathway, which simulates the migration of production from the baseline to the target pathway in a 'late-and-sudden' policy transition. This dynamic occurs as a consequence of sustained business-as-usual production, where companies delay meaningful emissions reductions. As a result, abrupt policy interventions become necessary to meet climate goals, forcing companies to compensate for this overshoot by reducing production more aggressively than required under the climate target pathway (see Figure 1).

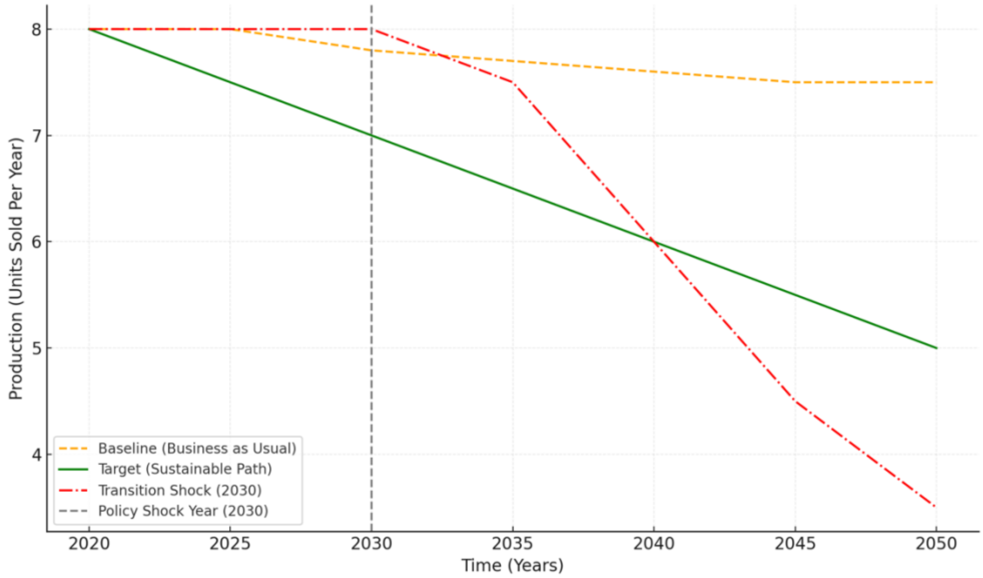

Figure 10: TRISK decarbonization pathways of carbon intensive production under different scenarios

Consequently, TRISK evaluates the misalignment of firms' planned carbon-intensive production with a Paris-aligned scenario pathway. Late and sudden policy action compels firms to decarbonize. Each firm follows its own production pathway, adjusting to compensate for misaligned production. In aggregate, sector-level production aligns with scenario-based technology targets and the overall carbon budget.

The second layer interacts with the company's decarbonization pathways with real economic projections on costs, price, and general economic developments, as well as company's financial risk profile. The production trajectories across various scenarios serve as the foundation for calculating firm net profits. For a given firm *i* and year *t*, net profit is derived by multiplying the production volume by the unit price and unit cost of the corresponding production technology *s*

$$Net\ Profit_{i,t} = production\ volumei_{i,t,s} \times \left(unit\ price_{t,s} - (unit\ cost_{t,s} + carbon\ tax_{t,s})\right)$$

Company production trajectories from climate scenarios drive the majority of the impact on profits.[9] Carbon tax is applied as an additional emissions cost per unit of production. When complete information on both prices and costs is lacking, the company's net profit margin (NPM) is used to fill in the missing data. The NPM reflects the most recent historical data available from Refinitiv Eikon. This approach, however, implies that the model does not dynamically account for changes in a firm's cost structure (e.g., CAPEX, OPEX) or its financing dynamics under different scenarios.

In the third layer, the model estimates companies' market and credit risk. Market risk is evaluated based on changes in the equity value under different climate scenarios. Specifically, company-level impacts are translated into profit projections based on technology-specific production shocks. These projections are then used in net present value models to assess changes in equity valuations.

Following Gordon's (1959) approach to future dividend flows, future profits are assumed to be distributed as dividend payouts to equity investors. Consequently, the NPV of a company equity is represented as the cumulative discounted sum of future net profits. The model applies the discount rate calculated based on the Capital Asset Pricing Model (Sharpe, 1964; Lintner, 1965).

For a given firm *i* and year *t*, using the cost of equity as the discount rate, the discounted net profit is calculated as:

$$Discounted\ net\ profit_{i,t} = \frac{\text{Net profit}_{i,t}}{(1 + discount\ rate)^t}$$

[9] Production trajectories ate integrated into the TRISK framework as shocks, with distinct approaches for carbon-intensive and low-carbon technologies. Carbon-intensive trajectories follow growth rates specified in the scenarios, while low-carbon trajectories are based on their relative share of total sectoral production. This method improves estimates for companies operating multiple technologies or planning future production expansions, even if they have no initial production.

The NPV of net profits for a given scenario is obtained by summing all future discounted net profits, with the dividend payout ratio set to 1:

$$Net\ Present\ Value_t = \sum_{shock\_year}^{2050} Div_{ratio} \times Discounted\ net\ profit_{i,t}$$

The company equity value change due to transition shock is then the percentage difference between NPV baseline and NPV shock. This metric thus constitutes a measure of company market risk because of transition shock:

$$Equity\ value\ change = NPV\ baseline - NPV\ shock$$

Credit risk is assessed by examining how changes in a company's NPV translate into financial portfolio losses through the probability of default (PD). Company-level valuation changes under the shock scenario are incorporated into a time-horizon-adjusted Merton credit risk framework to estimate the firm-level PD. PDs are computed for both the baseline and shock scenarios, with the key output being the difference between the two, representing the additional impact on company-level PDs due to the climate transition shock.

The probability of default (PD) is defined as the likelihood that the asset's value (i.e., equity value and debt) falls below its liabilities, representing the default threshold (i.e., the value of debt):

$$PD=\Phi\left(-\left(\frac{\log(\frac{V_0}{L})+(r-\frac{\sigma^2}{2})t)}{\sigma\sqrt{t}}\right)\right)$$

Here, Φ represents the CDF of the standard normal distribution. The expression inside the parentheses is the z-score, and $\Phi(z)$ gives the probability that a standard normal random variable is less than or equal to z. The asset value is represented by V_0 while the value of debt is L. r represents the risk-free rate, σ the equity volatility and t is the credit instrument maturity.

Contrary to the market risk (i.e., change in equity value) estimation, the credit risk PD change model relies on an additional data input - company financial risk profile - on top of the production and scenario data inputs. In particular, the adjusted Merton structural credit risk model estimates PDs utilizing counterparties' balance sheets, which include the market value of assets, liability structure, and asset volatility. The market value of assets is derived by adding the equity value (calculated using the NPV method under the DDM assumption) with book debt value. The liability structure is taken as fixed and based on the firm's most recent balance sheet data. Asset volatility is proxied using historical equity volatility over the past 10 years. This simplification assumes that historical patterns in equity volatility adequately reflect the uncertainty of asset values in response to transition shocks.

While NPV changes can be estimated for each profit-generating, technology-specific units (e.g., assets) of a company, the probability of default (PD) change model operates only at the whole-company levels. This distinction exists because the discounted cash flow model relies on technology-level profit pathways to calculate NPV changes for individual business units.[10] Conversely, the Merton structural credit risk model evaluates transition risk impacts on the PD of entire firm. This is achieved by aggregating NPV changes across all business units, weighted by their relative size, and using the aggregated NPV change as input into the Merton model to calculate a single, company-level PD change.

[10] For example, for a firm in the power sector operating across renewables, nuclear, and coal power generation technologies, the NPV is estimated separately for each of these technology-specific business units.

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