Chapter 3

Financial transition risks and the multiverse of mitigation pathways

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Abstract

This article proposes a novel methodology for forward-looking low-carbon transition risk assessment based on a large set of scenarios. We build upon the IPCC Assessment Report 6 scenario database to explore the types of transition pathways most prone to financial instability. We start by clustering scenarios based on the form of decarbonisation schedules and on the profile of their carbon price trajectories to generate a classification of mitigation pathways. We then select the best representative within each of our 50 clusters, which we simulate with a stock-flow consistent to quantify indicators relevant to low-carbon transition risks. We then tackle uncertainty on future macroeconomic developments by running each scenario on different calibrations corresponding to the five Shared Socioeconomic pathways. We finally deal with uncertainty on model parameters by generating these macroeconomic regimes with an important number of parameter combinations. In the end, we simulate several thousand trajectories that differ by (i) decarbonisation pathway, (ii) macroeconomic regime and (iii) parametrisation of the macroeconomic regime. We also use scenario discovery techniques to explore how low-carbon transition risks vary across decarbonisation pathways, macroeconomic regimes and parametrisations. We find that while most decarbonisation profiles lead to mild transition risks, a handful of scenarios lead to strong instability potentials across states of the world. These scenarios are either delayed-action or deep-decarbonisation pathways featuring steep carbon price schedules.

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Introduction

As emphasised by the IPCC (2022a), the low-carbon transition will require much more than marginal adjustments to our current fossil-intensive development models. From electrification to sweeping energy efficiency improvements through the shift to sufficiency in our ways of life, keeping global warming below 1.5 to 2°C will require transformative changes. However, the IPCC has always insisted on the diversity of possible pathways compatible with Paris climate targets (IPCC 2022a). Paraphrasing de Haan et al. (2016), there are "Many Roads to Rome" for the same decarbonisation target. A good illustration of this diversity of transition pathways is the high number of decarbonisation scenarios reviewed by the IPCC. The AR6 surveys no less than 1,500 scenarios, around 800 of which are compatible with below-2°C global warming. A suite of around 20 models generates these scenarios, with often several frameworks simulating scenarios with similar narratives and core assumptions. These variants can provide quite different pictures of a transition path, with different climate policies, energy mix changes, macroeconomic policy costs, land use, and many other outcomes (IPCC 2022c).

On the one hand, this diversity of pathways is reassuring from a policymaking standpoint because it suggests that there may be a degree of flexibility in achieving climate targets. However, it creates uncertainty for many economic agents. For instance, whether an investor should bet on large-scale renewable energy deployment in the short run or on gas for short to medium-run developments is challenging to disentangle from scenarios alone. The same goes for the value of carbon, which varies vastly from one model to another. This uncertainty is a well-mapped topic within the Integrated Assessment Model (IAM) literature (Tavoni and Valente 2022; van Asselt and Rotmans 2002), which has explored how scenarios were sensitive to *ex-ante* assumptions (Gillingham et al. 2018), the models used to generate the scenarios (Kriegler, Petermann, et al. 2015), or the definition of the baselines (Marangoni et al. 2017). In the face of a possibly extensive range of outcomes, the IAM literature has insisted on considering various scenarios from many modelling frameworks to map related uncertainties as exhaustively as possible (*e.g.* Marangoni et al. 2017).

The uncertainty around the precise unravelling of the transition recently emerged as an important topic regarding the issues of asset stranding and low-carbon transition risks for finance. Stranded assets are those (natural, physical or financial) most at risk of losing value along a transition path (Caldecott 2017). In contrast, financial low-carbon transition risks relate to the risk of financial instability or crisis as the economy decarbonises (Carney 2015). As put by Semieniuk, Campiglio, et al. (2021), three factors drive these risks: climate policy, technological displacement and changes in consumer preferences. These three factors are characterised by deep uncertainty (Chenet, Ryan-Collins, and van Lerven 2021) and map almost one-to-one the realms of uncertainty highlighted by the IPCC that we mentioned above. Hence a necessary exploration of many different scenarios in assessing low-carbon transition risks (FSB and NGFS 2022).

If some approaches have embraced the diversity of transition pathways in assessing financial transition risks (Battiston, Mandel, et al. 2017; Battiston, Monasterolo, Riahi, et al. 2020; Roncoroni et al. 2021), most scenario-based exercises have relied on a different strategy. "Climate stress tests" have mostly built on a handful of scenarios and used a small number of models to assess transition risks (T. Allen et al. 2020; Vermeulen et al. 2021; ECB/ESRB Project Team on climate risk monitoring 2022). In particular, the workhorse approach in the field, proposed by the Network for Greening the Financial System (NGFS), has proposed a small number of scenarios (8 in the first scenario vintage (NGFS 2020a), 6 in the most recent one (NGFS 2021b)), generated by three Integrated Assessment Models (NGFS 2021b). This choice was intended to provide regulators with a readily available discussion tool with regulated institutions and to avoid too large an assortment of pathways in running regulatory exercises (Clerc, Bontemps-Chanel, et al. 2021).

However, it has not been demonstrated whether these approaches fully map the extent of uncertainties surrounding the transition that would be relevant to studying low-carbon transition risks. So far, the literature has mostly made a difference between "orderly" and "disorderly transition", with an emphasis on the timing of implementation of climate policies and technological change. "Orderly" transitions are pathways in which climate policies start early, are easily anticipated, where technological displacement is limited or easy to navigate by economic agents or with less stringent climate targets. "Disorderly" transitions, by contrast, are pathways in which climate policies are introduced late, suddenly and are unanticipated by agents, or where technological displacement is substantial. They represent disruptive states of the world that should be avoided from a societal standpoint. However valid, this dichotomy may only partially overlap with uncertainties regarding decarbonisation's precise pace and shape. For instance, scenarios (or scenario variants yielded by distinct IAMs) for the same climate target can exhibit a wide array of decarbonisation timings, differing in technological choices, emission reduction timing and economic activity. The implications in terms of transition risks are likely to be different, either in terms of intensity or regarding the sectors that will be affected (Gasparini, Baer, and Ives 2022). Furthermore, at the energy system level, a scenario involving gas as a bridge technology before the complete introduction of renewables will likely have less impact on fossil fuel companies than a scenario in which renewables are introduced early and quickly (Coulomb, Lecuyer, and Vogt-Schilb 2019). Hence, there is a dire need to explore various scenarios to better assess transition risk potentials along transition paths.

Thus, this paper proposes a novel methodology to assess low-carbon transition risks for a large number of transition pathways in order to account for three levels of uncertainty.

We first deal with uncertainty regarding future macroeconomic variables and business-as-usual decarbonisation dynamics by considering the five "macroeconomic worlds" embedded in the Shared Socioeconomic pathways (SSP). The SSPs are high-level ("meta-") scenarios embedding macroeconomic, societal and technological hypotheses on the unravelling of the 21st Century in the absence of climate policy. These assumptions imply greater or lesser obstacles to decarbonisation, which may alleviate or worsen transition risks for finance. We reduce SSPs to a mean growth target in a no-policy scenario and to an exogenous reduction in carbon intensity meant to match no-policy emissions.

We then deal with uncertainty regarding mitigation pathways (MP) and corresponding climate policies by taking advantage of the large variety of pathways in the IPCC scenario repository. After reducing the scenarios to their emission and carbon price schedules, we classify them into fifty clusters representing "typical" transition pathways thanks to a functional clustering algorithm. Across these clusters, we select fifty best representatives for our analysis.

We then simulate these scenarios with a stock-flow consistent model amenable to the emulation of transition pathways described in Daumas (2022) (Chapter 2). This framework allows the simulation of many scenarios at a relatively low computational cost. To make for the parametric uncertainty embedded in this model, we further generate 500 sensitivity calibrations for each scenario that we simulate to observe the dependence of our result on chosen parameters. We additionally simulate each MP along each SSP. We consider a sample of 125,000 simulations, 2,500 for each scenario (around 500 sensitivity calibrations per SSP). We use this sample to characterise low-carbon transition risks across all SSP-MP pairs through various outcomes.

Our findings indicate that transition risks for finance remain contained for many SSP-MP pairs we study, including MPs with high climate ambition and relatively high carbon price schedules. More precisely, Banks are significantly affected only in a minority of MPs. The picture is less favourable for non-bank financial agents, which incur more significant losses for a larger swath of projections. The most adverse MPs, overall, feature either very sharp decarbonisation dynamics in the short run, or, most notably, a low climate policy efficiency with respect to climate ambition. In other words, scenarios in which very high carbon prices must be implemented to achieve low or mid-range climate targets feature the highest transition risks content. We further show that acute transition risks can emerge far beyond the short run and last over extended periods, both for Banks and non-Banks. It highlights that the transition dynamics can prompt periods of financial fragility. However, our results suggest that financial low-carbon transition risks are reduced except for very adverse scenarios and that adequate regulatory efforts may not represent a brake on transition dynamics.

We further show that SSPs affect results in two ways. SSPs implying more rapid reductions in carbon intensity are more prone to "green bubble" patterns because they give an advantage to Incumbent high-carbon technologies. Indeed, they reduce the profitability and financial viability of new, disruptive low-carbon projects. Furthermore, high-carbon reduction dynamics interact with growth assumptions. SSPs with rapid carbon intensity reductions and high growth exacerbate green bubble patterns by putting more investment pressure on green technologies. In contrast to the *ex-ante* assumption they embed, SSPs with higher obstacles to mitigation in their narrative do not necessarily entail more adverse outcomes on financial variables. This feature emerges notably because of more favourable growth assumptions, higher growth allowing financial agents to grow away from financial disturbances.

Our paper speaks to various literatures. We first expand the methodology of long-run climate stress tests (NGFS 2022; ECB/ESRB Project Team on climate risk monitoring 2022; Vermeulen et al. 2021; Fazekas et al. 2021) by increasing the number of scenarios explored in transition risk assessments. Furthermore, as in Daumas (2022) (Chapter 2), we explicitly account for the interaction between the financial sector and the ongoing low-carbon transition by modelling financial agents' behaviour along the transition path. Only very few papers belonging to the stock-flow consistent (Monasterolo and Raberto 2018; Gourdel, Monasterolo, Dunz, et al. 2022; Dafermos, Nikolaidi, and Galanis 2018) and agent-based (Lamperti, Dosi, et al. 2018; Lamperti, Bosetti, et al. 2019) literatures have carried out this endeavour.

We also relate to this former literature by deploying a stock-flow consistent model of decarbonisation trajectories. Stock-flow consistent and agent-based models have been applied to physical (Lamperti, Bosetti, et al. 2019) and transition risks (Dafermos, Nikolaidi, and Galanis 2018; Dafermos, Monserand, and Nikolaidi 2022; Gourdel, Monasterolo, Dunz, et al. 2022). However, to our knowledge, stock-flow consistent and agent-based models have yet to be used to simulate fully-fledged decarbonisation scenarios. Our model is dedicated to this purpose and examines low-carbon transition risks along existing decarbonisation scenarios.

We finally call out to the broader Energy-Economy-Environment integrated assessment literature. We do so first by building on the large variety of scenarios it has produced and by applying them to research questions outside the focus of the community. Typical IAMs do not incorporate a financial sector (Keppo et al. 2021) and cannot provide relevant metrics for the study of low-carbon transition risks, leading to many calls to bridge this gap from the research community (Battiston, Monasterolo, Riahi, et al. 2021; Keppo et al. 2021; Mercure, Knobloch, et al. 2019). We take on this research agenda by directly tying links between decarbonisation scenarios and methodologies amenable to studying transition risks.

Our paper is structured as follows. Section 1 reviews the literature in more detail to motivate our approach further. Section 2 briefly describes the model we will deploy for our analysis. Section 3 discusses our simulation approach, while Section 4 presents our indicators of interest. Section 5 presents our results before we conclude.

1 Literature review and motivation

Transition risks have given birth to a rapidly developing literature, prompting many theoretical and methodological innovations (see Daumas 2023, Chapter 1 for a review). Notably, “climate stress tests” of various flavours (Cartellier 2022) have emerged as the workhorse methodology to explore transition risks. Facing deep uncertainty regarding the modalities of the transition — technological change (Grubb, Drummond, and Hughes 2020), climate policy implementation (Batten, Sowerbutts, and Tanaka 2016), and consumer preference shift (Semieniuk, Campiglio, et al. 2021), these climate stress tests have relied on scenario-based approaches to study short- or long-run transition risks. Because this paper deals with whole transition pathways, we focus on the research focused on the latter. The related literatureis divided into three main strands.

The more traditional integrated assessment modelling literature has mainly studied transition risks through the lens of asset stranding. Based on various decarbonisation scenarios, these studies have primarily consisted in quantifying the financial losses incurred by high-carbon non-financial companies along the transition path. They usually reach significant potential losses in balance sheet losses due to premature decommissioning (Fisch-Romito et al. 2021) or foregone profits (Mercure, Pollitt, N. R. Edwards, et al. 2018). These losses depend positively on the intensity and delay of climate policies and are lower if agents are supposed to be forward-looking (Daumas 2023). However, because the models used in these pieces of work do not represent the financial sector, the transmission channels from asset stranding to transition risks are not modelled. It calls for using models amenable to stranded assets but including the financial sector (Botte 2019; Hafner et al. 2020; Battiston, Monasterolo, Riahi, et al. 2021; Keppo et al. 2021).

Financial supervisors have proposed approaches to include the financial sector in the analysis. These methods are mobilised in the context of large-scale, data-intensive regulatory exercises. They typically involve several coupled models, usually an integrated assessment model, a macroeconomic model, and a module computing finance-relevant outcomes (*e.g.* T. Allen et al. 2020; Vermeulen et al. 2021). These works include applications of the NGFS methodology based on six overarching scenarios (Bertram, Jérôme Hilaire, et al. 2020) that serve as a reference point for regulators and financial companies (NGFS 2021b; NGFS 2022). These works usually point at relatively low transition risks, even in the case of delayed-action scenarios, concentrated in the years following climate policy's introduction (ECB/ESRB Project Team on climate risk monitoring 2022). In particular, they highlight the incommensurability of physical risks (*i.e.* financial losses due to climate damage) compared to transition risks. Hence a trade-off explicitly favouring fast transitions and aiming for ambitious decarbonisation targets (Carney 2015).

However, these studies come with some limitations. First, although they generate results relevant to finance and financial instability, the models mobilised in the above do not represent the interactions between the financial sector and the real economy. Financial modules translate transition developments into signals that typically do not feed back onto the economy (see ESRB (2020) for an exception). They, therefore, do not capture the “double materiality” of transition risks, according to which transition pathways are not only exogenously applied to the financial system but are also shaped by the reaction of the financial sector (Chenet, Ryan-Collins, and van Lerven 2021; Gourdel, Monasterolo, and Gallagher 2023). Second, these exercises rely on tools relatively resilient to shocks, which poses identification (T. Allen et al. 2020) and circularity (Borio, Drehmann, and Tsatsaronis 2014) issues. It also reduces relevant transition events to large macroeconomic shocks at one point (Batten, Sowerbutts, and Tanaka 2016), while the low-carbon transition will mostly be about medium-to-long-run structural change (Daumas 2023). Third, these methods do not address the issue of stranded assets (Jacquetin 2021). Finally, regulatory exercises have only made use of a reduced number of scenarios, between three (T. Allen et al. 2020) and six (ECB/ESRB Project Team on climate risk monitoring 2022), depending on whether the authors considered model variants of the same scenario. As noted by Daumas (2023) and FSB and NGFS (2022), such a reduced number of scenarios does not allow us to explore all the uncertainties related to the low-carbon transition and associated risks. In particular, the precise shape of decarbonisation schedules (Daumas 2022) (Chapter 2) or hypotheses about the evolution of the energy mix (Gasparini, Baer, and Ives 2022) can have a considerable influence on the extent of transition risks for the same decarbonisation target.

Some works have used different modelling approaches, notably stock-flow consistent (Dafermos, Nikolaidi, and Galanis 2017; Monasterolo and Raberto 2018; A. Jackson and T. Jackson 2021, among others) and agent-based (Lamperti, Dosi, et al. 2018; Botte et al. 2021) methods. Compared to supervision exercises, these studies rely on more behavioural models, with heterogeneous agents at various degrees of disaggregation. These models build on Schumpterian and post-Keynesian traditions that have traditionally emphasised the importance of the financial sector in economic dynamics. They typically include a built-in representation of financial relationships (notably credit contracts) and a representation of the interactions between financial and non-financial companies. They thus represent a promising complement in that they can provide insights into the evolution of financial stocks and the issue of financial instability. These models have mainly explored the effects of financial policies, like green bonds (Monasterolo and Raberto 2018), differentiated capital requirements (Dafermos and Nikolaidi 2021) or shifting consumption patterns (Dafermos, Monserand, and Nikolaidi 2022). Some works tackle the issue of physical risks (Lamperti, Bosetti, et al. 2019) or asset stranding (Botte et al. 2021). However, to the best of our knowledge, these applications have not used existing mitigation pathways (Daumas 2023) or have not focused on achieving climate targets (Gourdel, Monasterolo, Dunz, et al. 2022). They, therefore, do not provide insights into how macro-financial risks could emerge along transition pathways.

This paper intends to bridge the gaps identified above. First, it draws a link between the IAM literature and the transition risk field by considering scenarios from the IAM literature. To do so, it builds on the stock-flow consistent model proposed in Daumas (2022), which is amenable to the simulation of transition pathways achieving a climate target. The model includes a built-in representation of the financial sector and its reaction to sweeping structural changes as the economy decarbonises. We finally apply this methodology to many scenarios and calibrations to explore as many aspects of uncertainty as possible. Through this approach, we intend to pin down the conditions most prone to transition risks and the dependence of expected macro-financial risks on macroeconomic and parameter hypotheses.

2 The model

This study uses the model presented in Daumas (2022) (Chapter 2), FASM-ID (Financial Asset Stranding Model – Instability and Decarbonisation). The model is a stock-flow consistent framework of structural change dedicated to simulating transition pathways, initially applied to the scenario set provided by the NGFS.

2.1 General model description

FASM-ID is a seven-sectors SFC model of structural change and financial instability calibrated worldwide with a yearly time step. It depicts a process of low-carbon transition and associated macro-financial risks. To do so, it represents the progressive replacement of an Incumbent, high-carbon sector by Challenger companies investing in low-carbon technology. Because they rely on leverage and equity emissions, these sectors have liabilities towards the financial sector. The financial sector first comprises a banking branch that extends loans based on firms' demand. It also includes Non-Bank Financial Institutions (NBFIs) that provide equity finance. The banking sector pays financial incomes to households, which also receive wages in exchange for their labour for firms. An independent investment goods sector, wholly owned by households, provides investment goods. The government levies taxes, provides subsidies, and emits bonds to finance expenses that Banks and NBFIs buy. Finally, the Central Bank fixes the base rate, buys excess government bonds and provides advances to Banks if needed to close their balance sheets. Figure 1 provides a flow chart of the model.

2.2 Key mechanisms for financial instability

The model focuses on low-carbon transition risks implied by asset stranding and structural change along decarbonisation paths. We force the model to follow an exogenous decarbonisation pathway and apply a carbon tax on emitting firms to mimic the effect of climate policy. Decarbonisation emerges through investment in low-carbon capital, the lower utilisation of high-carbon capital, and decommissioning. Decommissioning high-carbon capital is our way to figuring capital asset stranding for firms (Daumas 2023; Caldecott 2017). For simplicity, the Challenger sector is the only one to invest in greenfield low-carbon capital. However, we assume that the

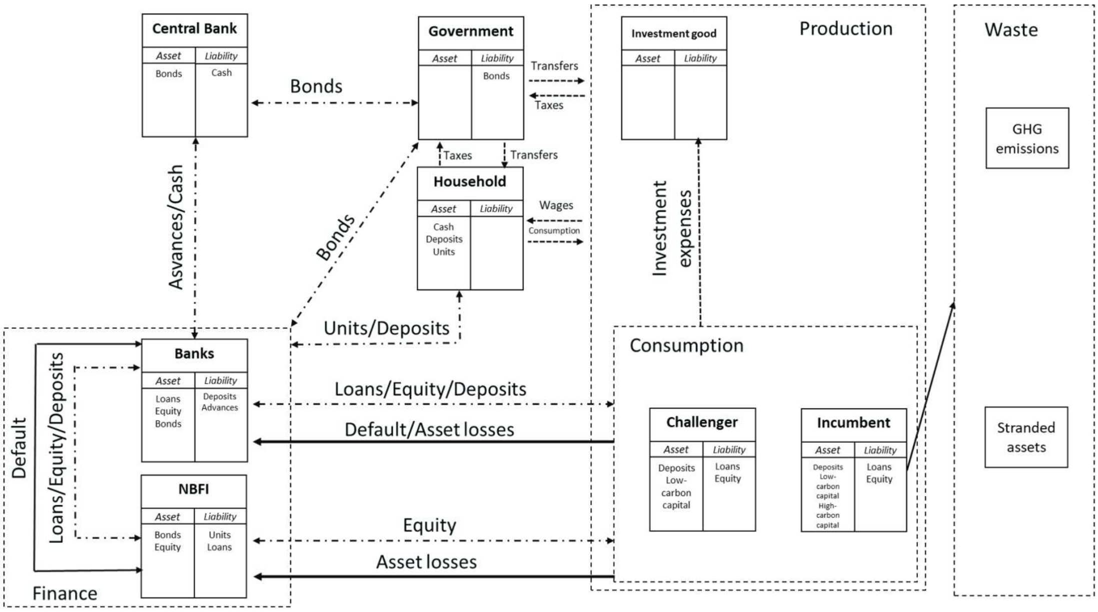

Figure 1: Diagram representation of FASM-ID. Dashed lines rperesent financial flows, while solid lines highlight transition risk exposures.

high-carbon sector can retrofit part of its capital stock in each period to avoid asset stranding. Figure 2 displays how we simulate the transition in the model.

In the model, financial instability emerges through various channels. Technological displacement will imply a fall in high-carbon firms' proceeds, resulting in a lower ability to pay back loans and, therefore, higher defaults. High-carbon firms will also be affected by asset stranding, which will affect their leverage, increasing the risk premium on their loans and limiting their ability to repay past loans. These mechanisms will affect Banks' balance sheets through their leverage and capital adequacy ratios. The carbon tax will also affect proceeds and firms' ability to repay their loans. Losses in market shares will decrease the demand for polluting firms' equity, limiting further cash inflows. It will also drive equity prices down, affecting NBFI's available liquidity and making their position more fragile. Finally, the model accommodates the possibility of "green bubbles" scenarios. Both the Challenger and the Inculmbent sectors being able to invest in low-carbon technology, they must take on additional loans. This increase, in general, may also make their position more fragile due to

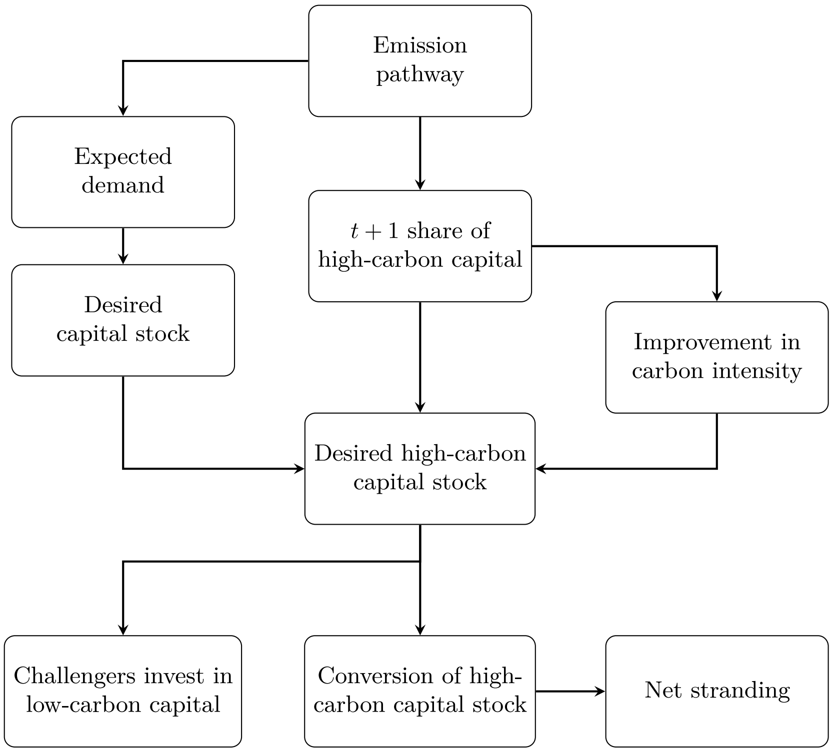

Figure 2: Representation of the transition process in FASM-ID

higher interest rates and if more than additional proceeds are needed to cover loan costs. Figure 3 summarises the main causality channels present in the model.

One important caveat regarding the exogenous application of carbon prices drawn from pre-existing scenarios onto other models should be considered. As noted by IPCC (2022c), the carbon price schedules produced by IAMs should be interpreted more as an overall measure of the climate policy stance and its disruption than as an outright carbon price set by the regulator. In some of these models, such carbon prices are shadow prices as usually encountered in linear programming or may bear little macroeconomic meaning when they are the outcome of partial-equilibrium frameworks such as bottom-up energy models. As a result, although we do consider these carbon prices as actual taxes levied onto polluting firms within the model's framework, it must be kept in mind that this interpretation is extreme, especially for extremely high carbon price schedules (more than US$15,000 in 2040) as produced

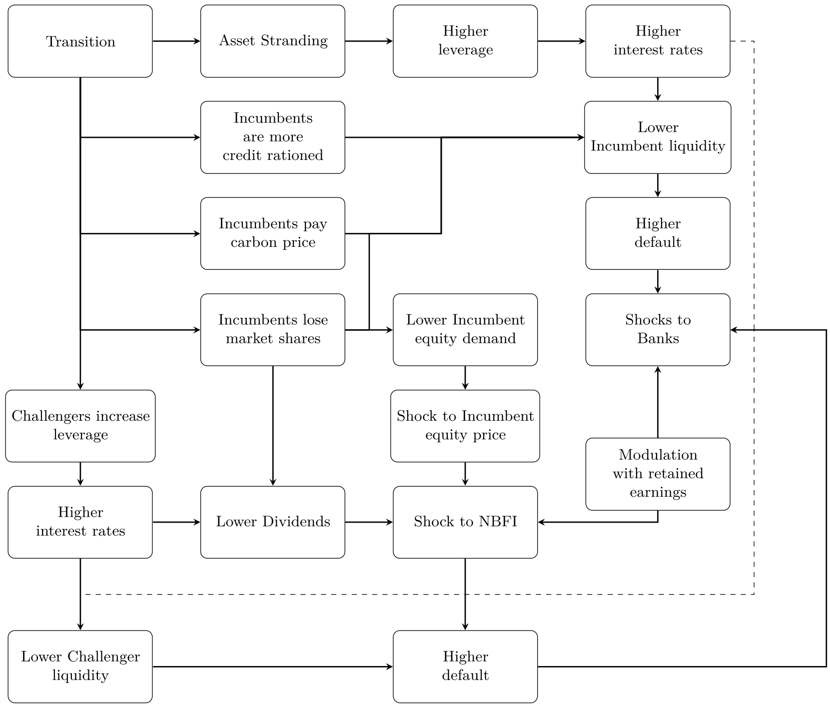

Figure 3: Causality channels to financial instability

by some IAMs. It is especially the case for partial equilibrium, bottom-up IAMs, such as POLES, which do not account for the second-round macroeconomic effects of carbon prices.

3 Simulation approach

Our approach aims to take advantage of the extensive array of decarbonisation scenarios to examine various transition profiles' low-carbon transition risk content. Figure 4 summarises our process.

We calibrate our model to match the five baseline Shared Socioeconomic Pathways regarding emission trajectories and GDP growth. We also make the model match some macroeconomic stylised facts and data not provided within the SSP framework but relevant to studying low-carbon transition risks (1). We then build a database of sensitivity calibrations (around 500 per SSP), which consist of deviations from the

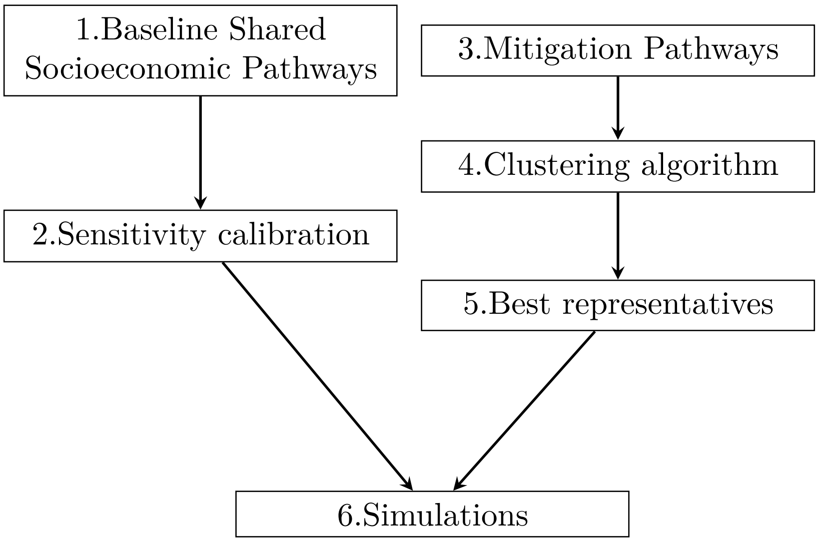

Figure 4: Summary of our simulation process

master calibration that yield similar macroeconomic dynamics. We do this to make for the uncertainty linked to our modelling framework around relevant parameters (2). We consider around 600 MPs from the IPCC database (3). Because some scenarios can be very similar, and to reduce the number of simulations necessary for this research, we use a functional clustering algorithm to group our transition scenarios into clusters with similar decarbonisation and carbon price trajectories (4.). Within each group, we select a "best representative" scenario for our simulations (5). We finally run all the selected scenarios for each macroeconomic world across all sensitivity calibrations and consider a range of well-chosen outcomes relevant to studying low-carbon transition risks (5). We detail each step further in the following.

3.1 Baseline calibrations

We consider the Shared Socioeconomic Pathways (SSPs) to build our baseline calibrations. The Energy-Economy-Environment (E3) integrated assessment literature developed the SSP framework based on the observation that many macroeconomic worlds could correspond to the same decarbonisation pathway or at least the same long-run decarbonisation target (O'Neill, Kriegler, Riahi, et al. 2014). SSPs are thus broad narratives about the unravelling of the 21st Century. They feature distinct macroeconomic, technological, societal and geopolitical hypotheses, which depend on whether mitigation or adaptation to climate change will be most challenging (see Figure 5). Five scenarios available on the IPCC repository[1] embody the SSPs. Like most scenarios reviewed by the IPCC, the SSPs are high-dimensional objects, with many outcomes drawn from large-scale integrated assessment models (IAMs). Our modelling framework is much more simplified, so we reduce the SSPs to two dimensions.

First, we consider the SSPs' emission schedules and force our model to match them in each period. To do so, we assume that our "Challenger sector" does not emerge in a world without climate policy. Instead, we suppose that the Incumbent sector benefits from an exogenous improvement in the carbon intensity of its production that allows it to match the emission schedule perfectly. This hypothesis allows us to keep tractable baseline values for our primary outcomes and maintain comparability across scenarios.

Second, we consider the mean growth rate between 2020 and 2055 for each SSP and calibrate the model to match it. SSPs also differ in terms of long-run growth assumptions, which we display on Table 2. SSP5, consistently with its narrative, maximises GDP growth at a yearly 4.3% rate on average. SSP1 adopts the second-highest growth assumptions, with 3.1% per year, on the ground that the deployment of low-carbon technologies allows for productivity gains. SSP2 and SSP4 adopt middle-ground assumptions, respectively 2.8% and 2.65% on average, close to existing projections. SSP4 has slightly lower growth due to the unequal development across nations supposed by its narrative. Finally, SSP3 features the lowest growth assumptions due to its narrative based on a lack of international cooperation and centring on national issues at the expense of trade and development. These assumptions are summarised in Table 1.

Unfortunately, SSPs do not provide hypotheses on relevant macroeconomic variables

[1] The database can be accessed at : https://data.ene.iiasa.ac.at/ar6/#/workspaces.

Figure 5: Classification of Shared Socioeconomic Pathways. Borrowed from O'Neill, Kriegler, Ebi, et al. (2017).

like inflation or public deficits. Neither do they *a fortiori* on pertinent metrics to financial low-carbon transition risks. As a result, and to avoid an unnecessary increase in the dimensionality of our exercise, we make the model target the same macroeconomic behaviour for a range of relevant macroeconomic and macro-financial variables as in Daumas (2022) (see Chapter 2 Appendix C.). More details on the calibration values are provided in Appendix B.

3.2 Selection of sensitivity parameters and ranges

The model in Daumas (2022) contains several behavioural parameters that affect the dynamics of transition risks. To make for this dependence on parameters and explore the dependence of transition risks on crucial dimensions of the model, we build sensitivity calibration around the main SSP parametrisations.

To do so, we adopt the same methodology as in Daumas (2022) (Chapter 2) and consider a set of parameters relevant to macroeconomic and financial dynamics. We then

Table 1: Economic growth assumptions embodied in SSPs

SSP	Name	Average economic growth (2020-2050)
SSP1	"Sustainable Development"	3.5%
SSP2	"Middle of the Road"	2.78%
SSP3	"Regional Rivalry"	1.93%
SSP4	"Inequality"	2.64%
SSP5	"Fossil-fuelled development"	4.3%

draw sensitivity intervals around the values retained for the master calibration. We proceed in two steps. We first draw a 90%-110% interval around each parameter and run 10,000 simulations for each master calibration. We retain only simulations remaining sufficiently close to the behaviour of the master calibration, *i.e.,* within a 20% range of the values targeted in the master calibration, depending on the outcome.[2] We then use a Morris method to determine which parameters affect the probability of retaining a given calibration to help us choose meaningful parameter ranges to select our sensitivity calibrations. For the most critical parameters, we adopt 95%-105%. We choose a 70%-130% range for all other parameters, a reasonable range found in other sensitivity analyses (P. Jacques et al. 2023). These differentiated parameter ranges intend to explore a breadth of values to make our sensitivity analysis more robust while allowing us to constitute a large enough sample of sensitivity calibrations. Appendix B. provides the value ranges for our parameters of interest.

We then use these ranges to sample parameter sets through Latin Hypercube Sampling and run simulations until we retain at least 1,000 sensitivity calibration for each SSP. 25,000 simulations were required. In the end, we ended up with a database of around 1,000 calibrations across our SSPs. To obtain a balanced dataset in the following, we draw a random 500 calibration per SSP, consider the mean trajectory for each outcome, and compute the corresponding variance. The importance of parameter variations will be assessed in Appendix. Each of these calibrations will be used as a baseline to simulate representative MPs that we take from the IPCC database.

[2]This tolerance margin was chosen as compromise between not drifting too far from the master calibration and exploring meaningful range of parameter values.

3.3 IPCC Scenarios and selection

The Working Group III IPCC (IPCC 2022c) reviews a wide range of decarbonisation scenarios provided by the IAM E3 literature. It synthesises their insights to inform policy choices regarding climate change mitigation. These scenarios are submitted to the IPCC by modelling teams from well-established institutions, ranging from the International Energy Agency (IEA) to specialised research labs (PIK, PNB…). Scenarios are specific to the institution or part of multi-model programmes such as intercomparison exercises.

The IPCC makes all these scenarios and their relevant outcomes publicly available, and we take advantage of this large scenario repository (Byers, Edward et al. 2022). The database features around 1,500 scenarios, simulated by approximately 20 different models. Among all these scenarios, about 800 are scenarios featuring emission pathways compatible with 1.5°C to 2°C global warming. These scenarios all feature some climate policies synthesised with a carbon price schedule. Hence, this "carbon price" variable should not be interpreted as a putative carbon price path; instead, it is a general measure of the intensity of climate policies necessary to achieve the climate objective.

As in the case of SSPs, IAM-generated scenarios are highly dimensional objects that we cannot fully reproduce with our simplified model. Therefore, reducing these scenarios to their emission trajectories[3] and carbon price paths allows us to explore how the shape and pace of decarbonisation dynamics and the intensity of climate policies affect transition risks. Unfortunately, some IAMs used by the IPCC suite, or some scenarios focused on regional dynamics, do not provide a straightforward measure of a "carbon price" at the world level that we need as a model input for our simulations. To avoid any mismatch, we dropped all of those scenarios from the database and ended up with a sample of 584 decarbonisation scenarios.

To reduce the dimensionality of our problem, we propose a classification of decarbonisation scenarios based on the profile of their emission schedules and their carbon

[3] Since our model does not feature negative-emisssion technologies, we build gross emission series.

price path to select "best representatives" within the IPCC database. To do so, we apply a functional clustering method. Functional clustering is the time-series equivalent of traditional clustering, whereby a data scatter is gathered into groups with similar characteristics. Functional clustering fulfills the same goals by grouping curves based on shape and level. Several methods exist, ranging from the depreciation of well-chosen measures (Ieva et al. 2013) to more complex likelihood maximisation algorithms based on the decomposition of curves into well-defined essential components or "splines" (Bouveyron and J. Jacques 2011). This paper uses the funHDDC algorithm proposed by Schmutz et al. (2018), based on likelihood maximisation and spline decomposition. We chose this algorithm first because the spline-decomposition method is better at capturing the dynamic profile of curves, which is crucial for our purpose. Second, a comparison exercise proposed by J. Jacques and Preda (2014) showed that funHDDC performed very well on curves with relatively monotonic behaviours, such as emission and carbon price schedules (see Schmutz et al. (2018) for more precision on funHDDC).

funHDDC supports bivariate clustering. As a result, we could have directly clustered MPs according to their emission and carbon price paths. We applied this method in the first instance. However, it resulted in a relatively low number of representative scenarios. We, therefore, used a two-step approach and clustered scenarios first by their emission schedule and then, within each emission cluster, based on the corresponding carbon price profiles. We chose to cluster by emission first to emphasise the importance of the emission reduction target in the design of scenarios, carbon prices usually being outcomes of the simulations. Also, it seemed more meaningful to first categorise scenarios based on the policy target and then classify them based on the policy intensity necessary to achieve each target.

This process yields 50 clusters. To select the best representative amongst each of them, we first consider an abstract "mean curve" for each cluster within the (Emission, Carbon Price) space, which we obtain by taking the mean (Emission Carbon Price) couple at each point in time between 2020 and 2055. For each scenario, we compute its distance[4] to the mean curve and consider the scenario closest to the mean curve the best representative. This process leaves us with 50 "best representatives" of the IPCC dataset. Because they are provided at a 5-year time step, we interpolate them to a yearly time step to make them consistent with our model's term structure.

3.4 Simulations

We implement this methodology through Python. For each SSP-Scenario couple, we start by solving the model to make it fit the emission schedule of the scenario with the master calibration. We proceed in two steps. We first solve for the development path of low-carbon energy compatible with the emission trajectory. For this purpose, we implemented a gradient descent method minimising the cumulated squared deviation from the reference trajectory.

Our algorithm was not able to converge for all our sensitivity calibrations.[5] Therefore, our final dataset is not composed of precisely 125,000 simulations ($50 \times 500 \times 5$) but of around 100,000 simulations across SSPs, sensitivity calibrations, and decarbonisation scenarios. The following section discusses the different outcomes we will consider and how we relate them to SSPs and decarbonisation scenarios.

4 Outcomes and indicators

Given the many scenarios we consider and the many possible outcomes our model can yield, we synthesise our results and relate them systematically to our inputs. We start by depicting how we classify SSPs and our MPs with *ex-ante* measures of transition risks. We present our outcomes of interest, which will measure *ex-post* transition risks, *i.e.* the "actual" realisation of transition risks and financial instability potentials after the scenario is simulated.

[4] We consider a square norm normalised by standard errors at each point in time.

[5] In particular scenarios 1 (POLES-ENGAGE, EN_NPi2020_600) and 35 (EN_INDCi2030_600f) are highly stringent scenarios with the two highest carbon price schedules and were very difficult to simulate. Only 250 simulations are available for these two scenarios.

4.1 *Ex-ante* transition risk measures

To study our database, it is first helpful to draw an *ex-ante* classification of SSPs and MPs. Because we study many scenarios, it is essential to distinguish between scenarios expected to contain high transition risks and those implying *a priori* milder disruptions. This subsection depicts how we distinguish between scenarios and SSPs regarding *ex-ante* transition risk content.

4.2 Mitigation Pathways

The IPCC usually ranks scenarios based on their climate target, *i.e.*, whether a scenario implies emissions consistent with a 2°C, 1.7°C or 1.5°C warming at specific dates or with a peak temperature at certain periods. However, this ranking is insufficient for our exercise for two reasons.

First, among our 50 best representatives, multiple scenarios correspond to the same or similar climate targets. There is a need to differentiate between scenarios adopting, *e.g.*, a monotonous decarbonisation schedule and those exhibiting more staggered mitigation dynamics. For instance, as put forward by the NGFS (2022), delayed-action scenarios, which can feature very high decarbonisation rates over short timespans, can be expected to be riskier than early-action ones.

Second, our dataset features many different carbon price paths. Similar decarbonisation schedules may be achieved with more or less steep or staggered carbon price paths. Those with more severe (or suddenly more stringent) climate policy should be classified as riskier *ex-ante* than those with less stringent measures.

To differentiate across scenarios, we build a series of five indicators summarising the decarbonisation and climate policy profiles of our scenarios:

- "Decarbonisation Intensity" defined as ratio the between emissions in 2020 and emissions in 2050:

$$D_{Int} = \frac{Em_{2020}}{Em_{2050}}$$

- "Decarbonisation Steepness" measures the "staggeredness" of decarbonation dynamics. We define it as the absolute value of the maximum period-to-period decarbonisation rate over 2020-2055, which corresponds to the minimum growth rate of emissions – which can be negative – over the period:

$$D_{Steep} = 100 \times \left| \min_{i \in [|0:6|]} \frac{Em_{2020+5(i+1) - Em_{2020+5*(i+1)}}}{Em_{2020+5i}} \right|$$

- A measure of "Climate policy stringency", *i.e*, the increase in the carbon price between 2020 and the peak value of the carbon price. We consider the peak value and not the value in 2055 to make for non-linear carbon price paths that our scenarios may exhibit. We consider a log scale due to possibly very high carbon price values.

$$CP_{Str} = \log \max_{i \in [|0:6|]} \frac{CP_{2020+5i}}{CP_{2020}} 6$$

- An indicator of "Climate Policy Steepness", measuring the "staggeredness" of climate policy implementation, that we write as the maximum period-to-period carbon price increase rate over 2020-2050. We also consider a log scale.

$$CP_{Steep} = \max_{i \in [|0:6|]} \frac{CP_{2020+5(i+1)}}{CP_{2020+5(i)}}$$

- The "Start of the transition", namely the year of peak emissions:

$$Peak = \max_{i \in [|0:6|]} Em_{2020+5i}$$

The higher these indicators, the more transition risks a scenario contains *ex-ante*. For instance, a very ambitious climate target (high D_{int}) would require more sweeping change than transitions aiming at lower targets. Likewise, a transition with an overall higher carbon price schedule is riskier *ex-ante* than a pathway with a lesser climate policy stance.

[6] Some scenarios feature a zero carbon price at the beginning of the transition; in such cases, we considered the growth rate between the first non-zero carbon price and the prevailing price in 2050.

Figure 6 summarises the profile of each of our 50 best representatives along each of these dimensions. For readability, we display three graphs. Panel (a) displays emission trajectories, while Panel (b) describes carbon price paths. Panel (c) displays the profile of each trajectory along our five dimensions in the form of a parallel coordinate chart.

Regarding decarbonisation dynamics, our population of trajectories gathers a wide variety of decarbonisation intensities. Regarding decarbonisation steepness, our selection comprises a mass of scenarios spanning values between 10 and around 35% decarbonisation rates. Then, a population of more extreme methods exhibits period-to-period decarbonisation rates between 40% and about 70%. Although there is a clear correlation between Decarbonisation intensity and Decarbonisation steepness for most scenarios, some representatives can exhibit high steepness for modest decarbonisation targets. Panel (a) offers a more detailed view of decarbonisation dynamics along our transition paths by allowing us to grasp the precise shape of the decarbonisation schedule, which can be more or less concave, convex, sigmoid, or linear.

As for climate policy, the gradient is much broader across our scenarios, reflecting the significant uncertainties around the intensity of climate policy necessary to achieve decarbonisation targets (IPCC 2022c). Strikingly, scenarios with mild targets can exhibit very high carbon prices in the long run, with up to eight-fold increases between 2020 and the climate policy peak. Conversely, ambitious targets could be achieved with low carbon price paths. The same goes for the steepness of the ramping up of climate policies, with up to a five-fold increase in the climate policy stance in five years. Similarly to Panel (a), Panel (b) offers a more detailed view of carbon price paths. In particular, one of our scenarios exhibits a non-monotonous path, with a peak carbon price in 2040.

Finally, most of our scenarios imply transitions starting in 2020. Around five scenarios indicate slightly delayed transitions, beginning in 2025, while only one starts in 2030. This imbalance between early-start transitions and a more delayed course of events translates the relative novelty of these kinds of scenarios and related research

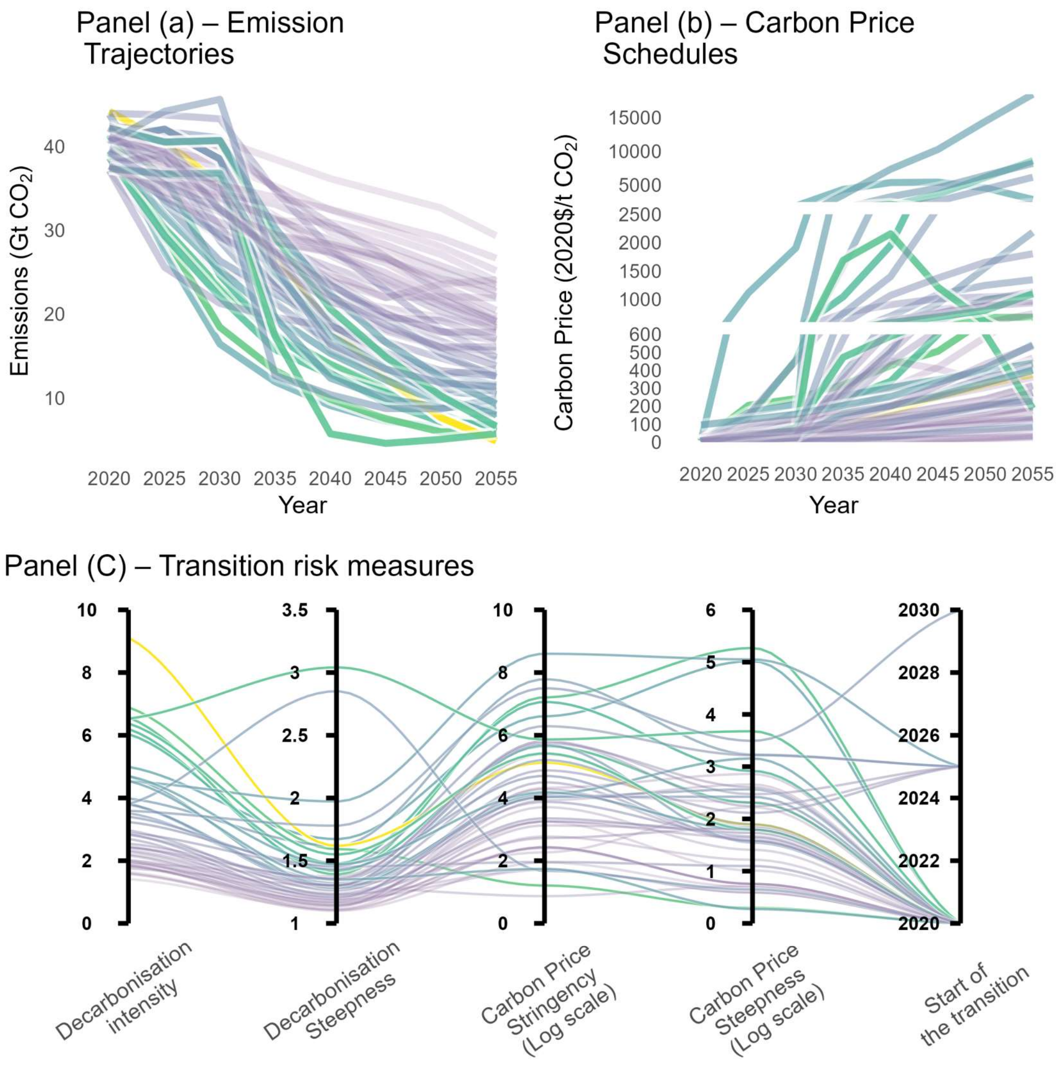

Figure 6: *ex-ante* transition risk profiles of the best representatives of our 50 clusters. Colors are indicative, and set according to the Decarbonication Intensity indicator.

questions, such as the issue of disorderly transitions due to the late and sudden introduction of climate policies (Batten, Sowerbutts, and Tanaka 2016; NGFS 2022).

Our scenarios will also vary regarding transition risks according to their underlying macroeconomic assumptions. Hence, we must discuss the *ex-ante* transition risk content of the five SSPs we take as base calibrations. In particular, a rough ranking of each SSP in terms of *ex-ante* transition risks will be helpful to facilitate the interpretation of results.

4.3 Ranking the Shared Socioeconomic Pathways

We rely on the classification provided by the IPCC (O'Neill, Kriegler, Riahi, et al. 2014) that we summarise in Figure 5. SSPs rank according to the challenges they pose to mitigation and adaptation. For instance, SSP5 is a challenging state of the world regarding mitigation, as it assumes an accelerated development of fossil fuels to maximise GDP growth. Hence, very high emission levels hamper the achievement of climate targets. By contrast, SSP1 represents a future in which technology and societal developments will feature the penetration of low-carbon technologies and a commitment to sufficiency. It is usually seen as the least challenging course of events regarding transition dynamics. For our purpose, we are primarily interested in challenges to mitigation. Within the SSP framework, they are well proxied by emissions. Figure 7 shows the different emission profiles for the various SSPs.

Using baseline emissions as a measure of mitigation challenge, SSP1 is a state of the world in which low-carbon transition risks are lowest, while SSP5 are highest. SSP3 exhibits the second-highest mitigation challenges, as per Figure 5. SSP4 and SSP2 are more difficult to disentangle, given the quantitative proximity of their emission schedules. Challenges to mitigation differ through time, with SSP4 implying faster emissions in the short run but less in the longer term than SSP2. However, the traditional SSP classification shown in Figure 5 ranks SSP2 above SSP4 in terms of challenges to mitigation. We, therefore, follow these guidelines. Table 2 summarises our ranking of SSPs, which also recalls the average growth assumptions matched in each SSP.

4.4 *Ex-post* transition risk measures

As in Daumas (2022), we first distinguish market and credit risk. Market risks concern asset prices and have an impact, within our model's structure, on Non-Bank

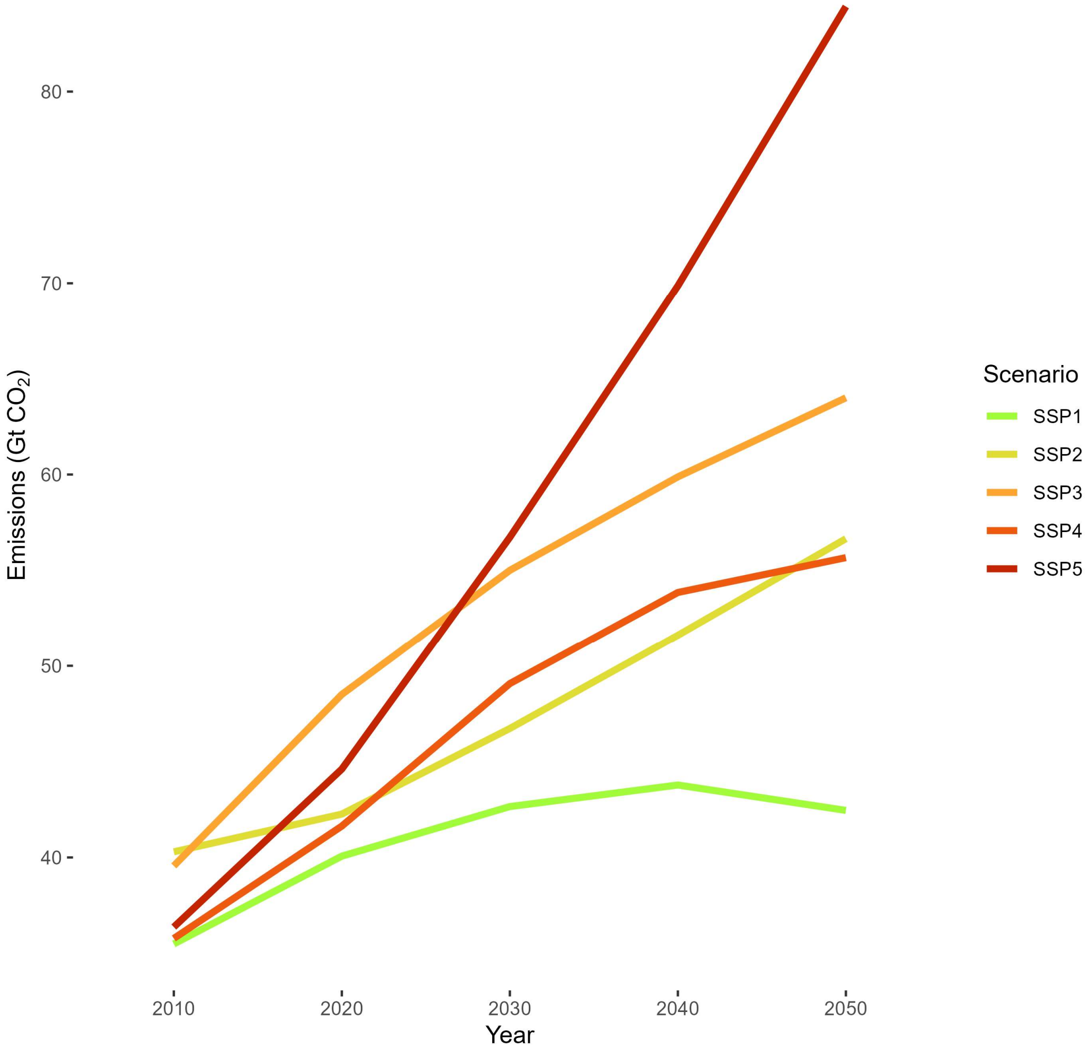

Figure 7: Emission trajectories of Shared Socioeconomic Pathways (No-Policy Baseline). Color indicates SSP. Different starting points are due to differences in marker models used to generate the baselines.

Financial Institutions. Credit risks, by contrast, transit through defaults on credits and will affect the viability of Banks' balance sheets.

We further separate transition risk realisations and vulnerability to transition risks. The first category concerns the financial shocks incurred by the non-financial sector due to technological displacement and climate policies. The model primarily

Table 2: Ranking of Shared Socioeconomic Pathways

Rank	SSP	Label	Average Growth Rate	Challenge to mitigation
1	SSP5	"Fossil-fueled Development"	4.3%	Very High
2	SSP3	"Regional Rivalry	1.9%	High
3	SSP2	"Middle of the Road"	2.8%	Medium
4	SSP4	"Inequality"	2.65%	Medium
5	SSP1	"Sustainability"	3.5%	Low

Notes: The ranking is by decreasing order

represents them through lower equity prices regarding market risks and higher default propensities. Transition risk vulnerability, on the other hand, sheds light on how realisations affect the financial sector. Indeed, the financial sector may navigate seemingly dire transition risk realisations if it can absorb shocks. For the current study, given its high dimensionality, we focus primarily on transition vulnerability indicators. In contrast, we will only discuss transition risk realisations to explain the patterns we find for transition vulnerability.

We use 11 indicators to study the financial sector's vulnerability to transition risks and divide them into two types. Across our sensitivity calibrations, we consider the average across simulations. We also consider a dispersion measure, discussed in Annex C.1. To correct for outliers, notably in computing the dispersion measure, we use the Winsorised mean at 95%.[7]

4.4.1 Magnitude Indicators

We first use *magnitude* indicators, which indicate the size of macro-financial shocks in terms of market and credit risk. For market risks, we consider the maximum default probability of NBFIs over the time horizon. Although it more exactly designates the financial counterparty risk associated with NBFIs, it is a direct translation of NBFI losses on financial markets. We thus adopt this denomination for convenience. The market risk indicator ρ_M thus writes:

[7] This method only affects the mean marginally, such that results in Section 5 are not different from using a non-Winsorised mean.

$$\rho_M = \max_{2020-2050} \varphi_{NBFI_t}.$$

For credit risks, we consider a similar indicator relating the minimal Capital Adequacy Ratio (CAR) obtained over the time horizon to the baseline value. In all our calibrations, the Capital Adequacy has a value of 0.18. Hence, we define the credit risk indicator ρ_C as:

$$\rho_C = 100 \times \frac{\min\limits_{2020-2050} CAR^* - \min\limits_{2020-2050} CAR}{\min\limits_{2020-2050} CAR^*} = 100 \times \frac{0.18 - \min\limits_{2020-2050} CAR}{0.18}.$$

Since the CARs we obtain are capped at 18%, the indicator lies within $[0, 100]$, with 0 denoting an absence of shock and 100 a full-blown financial crisis.

This indicator is nonetheless partial in that it does not allow determining whether shocks to Banks are due to an increase in default probabilities in the Incumbent polluting or the Challenger low-carbon sector. Although the literature has more focused on transition risks arising from asset stranding and losses in high-carbon sectors, our model can also, in principle, give rise to "green bubbles" dynamics, whereby low-carbon companies would spur instability due to high leverage (Nikolaidi 2017). We, therefore, build two complementary indicators gauging the maximum default probability in the Incumbent (ρ_{IN}) and the Challenger (ρ_{CH}) sectors along the run.

4.4.2 Timing indicators

A second range of indicators explores the timing of shocks to the financial sector. For credit risk, we measure the length of the (longest) period over which credit or the market risk indicator deviates from the value of 0.18 and reaches the minimum and the time step with the minimum credit risk indicator. We provide similar indicators for market risk but measure the period over which NBFI default probability is above average. These indicators allow us to determine whether shocks to the financial sector are short-lived or if a whole period of financial fragility emerges during the transition. It also indicates the timing of transition risks related to the start of the transition. We also compute these indicators for the Incumbent and the Challenger. With these definitions, the length of the high transition risk period will be centred around the period at which the apex of the measured risk is reached.

Whether disturbances emerge as a one-period, short-lived shocks bear distinct implications to a situation where financial troubles prevail over long hauls, even if the magnitude of related shocks is lower. Furthermore, it is usual in the transition risk literature to focus on transition risks in the short run, *i.e.*, immediately following the implementation of low-carbon policy (Semieniuk, Campiglio, et al. 2021) or the emergence of new technology (Vermeulen et al. 2021). By contrast, transition risks resulting from the build-up of imbalances at the macroeconomic level, in the spirit, *e.g.*, of Godley (2012), are relatively under-explored (Daumas 2023). Hence, timing indicators can provide insights into the time profile of longer-run transition risks. Table 3 summarises our set of indicators.

5 Results

We discuss here the main takeaways of our analysis. All results are values averaged across our sensitivity calibrations, with corresponding variances displayed when relevant.

5.1 Overview of transition risks

We start with an overview of the results in Figures 8 and 9. These scatterplots display, for all SSPs, our measures for firm and financial risks in a locus, with indicative thresholds for high risks.

Starting with firm risks, a sizeable proportion (73.6% across SSPs) of our best representatives implies low firm risks. For Incumbents or Challengers, high firm risk

Table 3: Indicators

Indicator	Notation	Description
Magnitude		
Market risk indicator	ρ_M	Maximum NBFI default probability over the scenario
Credit Risk indicator	ρ_C	Maximum Absolute deviation from 18% CAR over the scenario
Incumbent fragility	ω_{IN}	Maximum Incumbent default probability
Challenger fragility	ω_{CH}	Maximum Challenger default probability
Timing		
Market risk year	L_M	Length of period around market risk apex
Credit risk year	L_C	Length of period around credit risk apex
High market risk period	T_M	Time step of maximum market risk
High credit risk period	T_C	Time step of maximum credit risk
Incumbent Risk Year	T_{IN}	Time step of maximum Incumbent default probability
Challenger Risk Year	T_{CH}	Time step of maximum Challenger default probability
High Incumbent risk period	T_{IN}	Length of period around Incumbent risk apex
High Challenger risk period	T_{CH}	Length of period around Challenger risk apex

only emerges for a relative minority of scenarios. Some 17.2% of best representatives across SSPs carry high Incumbent risks only, while a tiny minority (3.2%) carry high Challenger risks only. Finally, a small scenario population has high Incumbent and Challenger risks (6% of the sample).

Furthermore, this figure highlights a relative dependence on the underlying SSP assumptions. SSP5 and SSP3 carry the highest risk for Incumbents, with SSP5 exhibiting the lowest risks for the Challenger. SSP2 and SSP4 show a middle-range pattern, with lower Challenger risk for the SSP4. Finally, SSP1 shows the lowest Incumbent risks and the highest Challenger risks for extreme scenarios and occupies a middle ground for low-risk scenarios.

This difference in pattern between SSP1 and SSP5 flows from our definition of SSPs. First, because, in SSP1, the Incumbent's carbon intensity decreases rapidly, the Challenger sector develops less and does not fully evict the Incumbent sector. Furthermore, asset stranding is lower in the Incumbent sector, reducing expansion potentials for the Challenger and available funding. As a result, in stringent scenarios where investment in low-carbon capital is high, the Challenger sector is more financially fragile than the Incumbent. The opposite goes for SSP5, in which the Incumbent sector is more penalised due to slow improvements in carbon intensity. This result illustrates the importance of competition between emerging low-carbon intensity

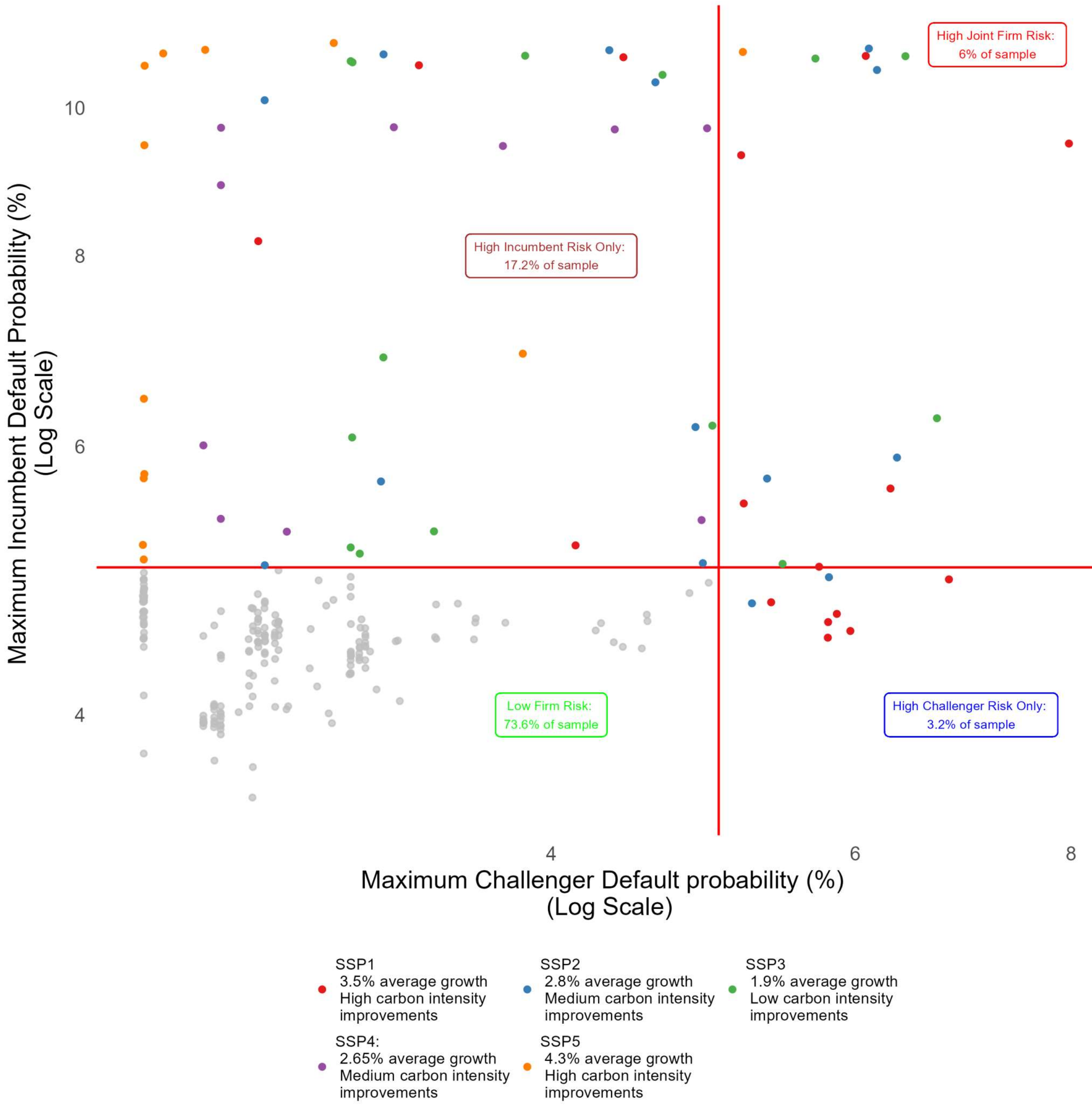

Figure 8: Overview of transition risks –Non-Financial Sector. Colors indicate the underlying SSP. The thick red lines are indicative risk thresholds. Only values beyond the thresholds are highlighted. The SSP characteristics are recalled for clarity. Take care of the log scale on both axes.

and Incumbents that may partially adapt to the transition in driving firm risks. A situation in which Incumbents can keep significant market shares can penalise the emergence of new activities which may generate dynamics similar to "green bubbles" (Borio, Claessens, and Tarashev 2021).

On the other hand, letting the Challenger develop will affect sunset activities. SSP5 implies very high growth rates, around 4.2% per year, more than 25% higher than those prevailing under SSP1. As shown in Daumas (2022) (Chapter 2), growth can benefit Banks' capital adequacy ratio by allowing firms to grow away from financial fragility. Given the Keynesian aspect of our model, this aspect may largely compensate for losses incurred by the financial sector. SSPs also differ in terms of average growth rates. This feature also affects results. SSP3 exhibits relatively high risk for both Challengers and Incumbents because of its low growth rates and modest carbon intensity improvements. On the other hand, for low-risk scenarios, the high growth rates of SSP5 allow the Challenger sector to develop with low risks.

Finally, carbon intensity improvements and growth rates interact, as illustrated by SSP2 and SSP4. These two SSPs carry relatively similar growth rates but with different carbon intensity improvements, concave for SSP2 and convex for SSP4, as per Figure 7. SSP4 carries relatively lower risks than SSP2, suggesting that long-run improvements to carbon intensity are more beneficial than in the short run. Furthermore, the lower growth rate in SSP4 may shield the Challenger sector from the rapid (and risky) development that would prevail in higher-growth scenarios like SSP1.

All this translates differently into financial risks, as shown in Figure 9. Credit risks are overall very low across best representatives, ranging between 1 and 3%, with a relatively high dispersion across SSPs. This behaviour is consistent with the results shown in Daumas (2022) (Chapter 2), whereby Banks are relatively resilient to transition risks for low- firm-risk scenarios. However, a small population of scenarios (around 10%) exhibit very high credit risk. These risks come with high market risk.

Market risks are more spread upwards, consistent with the results in Daumas (2022)

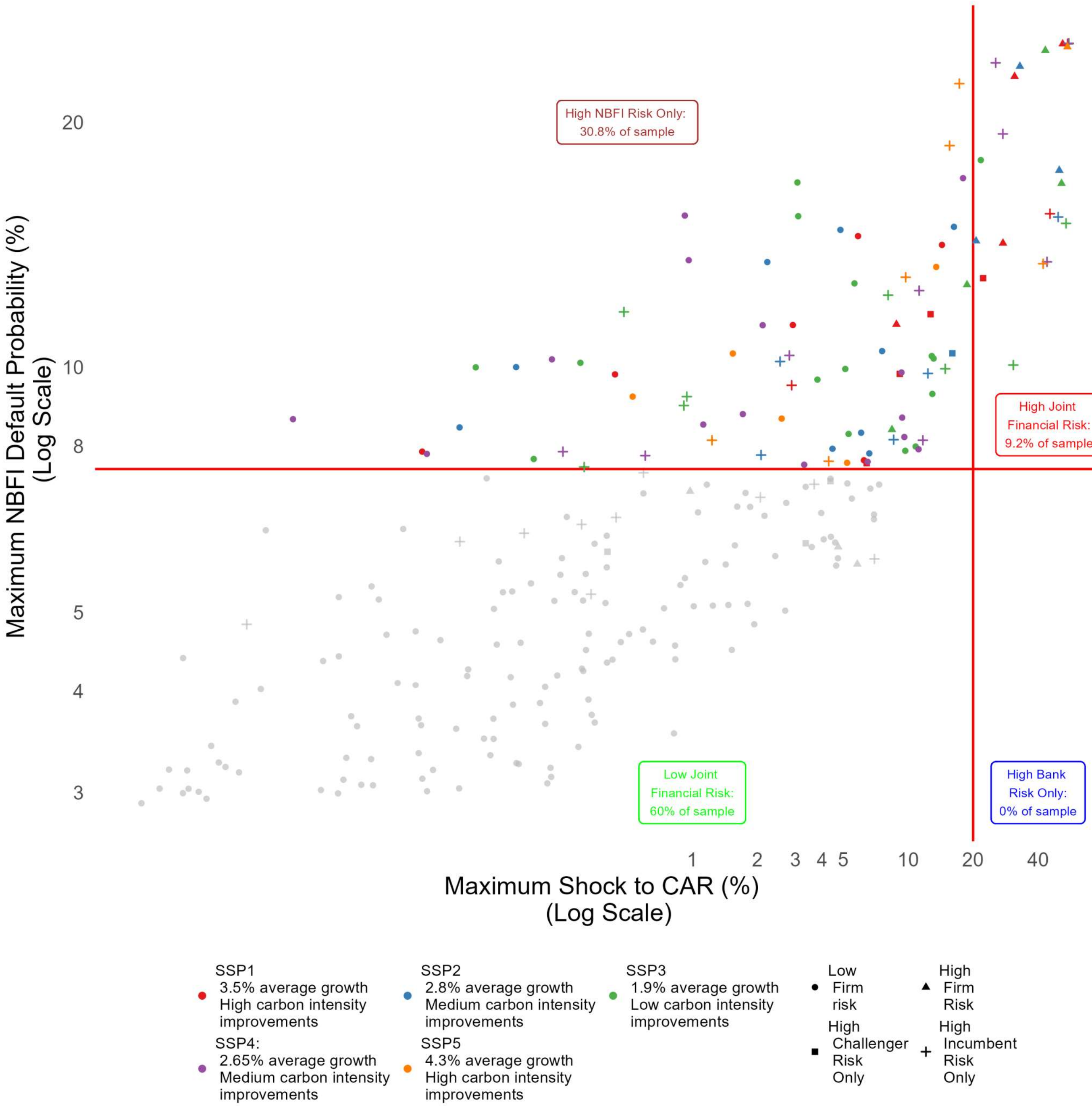

Figure 9: Overview of transition risks –Financial sector. Colors indicate the underlying SSP. Shapes denote whether scenarios are in the higher quadrants of Figure 8 and provide a view of the overlap between the two figures. The thick red lines are indicative risk thresholds. Only values beyond the thresholds are highlighted. Take care of the log scale on both axes.

(Chapter 2), and more dispersed across scenarios than credit risks. A relatively large population of scenarios stand above the indicative threshold of 10%, showing the higher fragility of NBFIs in the model. We also see, overall, a general correlation between market and credit risks, which may suggest the presence of amplification effects.

There is a high degree of overlap between Figures 8 and 9, with a sizeable share of scenarios in the high firm risk quadrants found in the high financial risks zones. However, the source of high financial risks can differ across scenarios. While Incumbent risk seems to drive financial risks in most cases, some scenarios associate high Challenger risk and high financial risk. Hence, financial risk can emerge both from sunrise and sunset industries alike, depending on the scenario.

Finally, it is noteworthy that many high-risk scenarios neither feature high Incumbent nor Challenger risk. This is attributable to two elements. First, the source of financial risks comes more from changes in asset prices. The latter can fall even if default probabilities do not increase much because loans are repaid before dividends, whose level directly affects the attractiveness of equity investment and thus asset prices through lower demand for equity. Second, like in Chapter 2, for credit risk, shocks to CAR can also emerge in case of rapid Challenger development alone through a transitory increase in Banks' exposures. Finally, conversely, some high firm risk scenarios do not necessarily translate into high financial risks: like in Chapter 2, the financial sector can absorb shocks under some circumstances.

A first important takeaway from our results is that from the standpoint of firm and financial risks, there is a large proportion of MPs with low or medium transition risks, representing "feasible" scenarios from the perspective of financial instability. Yet, the population of problematic scenarios is far from anecdotal. It begs us to examine the characteristics of these scenarios compared to their less risky counterparts. Furthermore, interestingly, our results only partially match our *ex-ante* ranking of SSPs based on their transition risk content. Because we assume a Challenger-Incumbent structure to depict the low-carbon transition, SSPs advantaging the Incumbent relatively more can carry significant risks. Because the Challenger needs to develop, it represents an ever larger share of financial institutions' exposures. If the sector is more fragile, it results in higher NPLs and more significant asset losses. Given that SSPs advantaging the Incumbents exhibit higher credit risks on average, it suggests that, for this type of risk, slowing down the development of new activities, or protecting Incumbents may result in higher financial risks than letting sunset industries entirely disappear.

Building on this discussion, we explore transition risks in more detail in the following. For brevity, we focus on financial risks only, with results on firm risk and policy costs displayed in Appendix C.

5.2 Linking *ex-post* risks with *ex-ante* risk indicators

Since we are interested in the relationship between scenario characteristics and our outcomes, we link our *ex-ante* transition risk measures to our *ex-post* transition risk measures.

5.2.1 Magnitude

We first discuss the magnitude of financial risks. Because Banks are affected by market risks, through NBFI leverage, we first discuss market risks to highlight possible amplification effects.

Results are shown in Figure 10, which follows the parallel coordinate template used in Figure 6 with the outcome of interest added to our *ex-ante* transition risks metrics and results split across SSPs. As in the above, results are mean values across simulations.

Across SSPs, 3 to 4 scenarios exhibit risk metrics above 15%, while around 5 stand between 7.5 and 15%. Although a majority of scenarios stand as "feasible", a substantial proportion falls even beyond the boundaries drawn by NGFS scenarios (Daumas 2022, Chapter 2). The severity of market risk mainly follows the stringency of climate policy. The carbon tax burden reduces dividends, which affects NBFI default through lower cash flow and decreases. However, the high NBFI risks emerge from the scenarios with the highest decarbonisation steepness, although their carbon prices are low. In these cases, the brisk shift towards low-carbon technology entails very high losses on equity, diminishing available liquidity.

Due to amplification mechanisms, these differences across SSPs in terms of market risk may partly explain differences found in credit risks, to which we turn now. Results are displayed in Figure 11.

A sizeable proportion of scenarios do not give rise to high credit risks, with shocks below 10%. These scenarios feature low low to high climate ambitions and low to medium-high carbon prices. This pattern is highly reassuring regarding the financial feasibility of MPs since the economy seems to be able to accommodate even high climate ambition with relatively high carbon price levels.

We find a population of problematic scenarios, some leading to an outright financial crisis – a 50-60% credit risk in our model means that Banks reach the prudential value of 8% CAR over the run and that the government had to step in to bail them out. However, severity varies across SSPs. Notably, SSP5 only exhibits three highly problematic scenarios, while SSP3 and SSP1 seem more adverse. SSP2 and SSP4 hold a middle ground, with SSP4 showing relatively low transition risks. Across SSPs, these problematic scenarios feature high carbon prices or steep decarbonisation dynamics and delayed action until 2025 or 2030 for some. In this latter case, credit risks are high but contained overall.

These scenarios mix a high carbon price with middle-ground climate ambition, steepness, and a sharp period-to-period carbon price increase. Hence, they suppose that climate policy is inefficient and comes with an extreme rise in carbon prices, in the sense that substantial policy pressure should be imposed from some point in time onwards to reach even a mild climate target. This feature implies that the carbon tax burden onto Incumbents is disproportionately high over a longer duration, affecting Banks directly through higher NPL.

The impact of delayed action shows significant differences across SSPs. In SSP1 to 3,

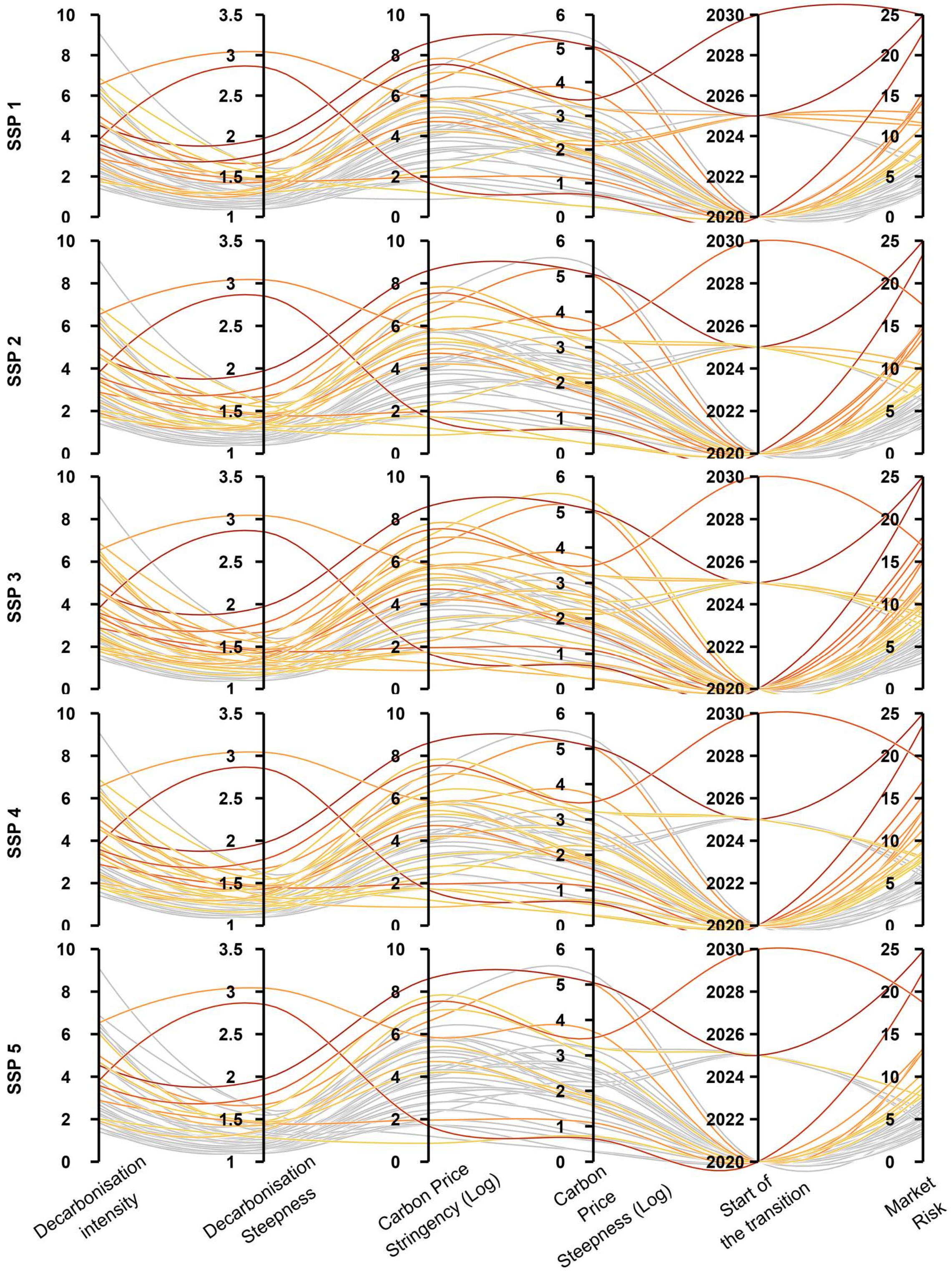

Figure 10: Mapping between market risks and scenario characteristics. Each line joins a combination of scenario characteristics with the value of the market risk indicator, which shows on the far-right axis. Colors indicate market risks, with only scenarios above the 7.5% threshold highlighted.

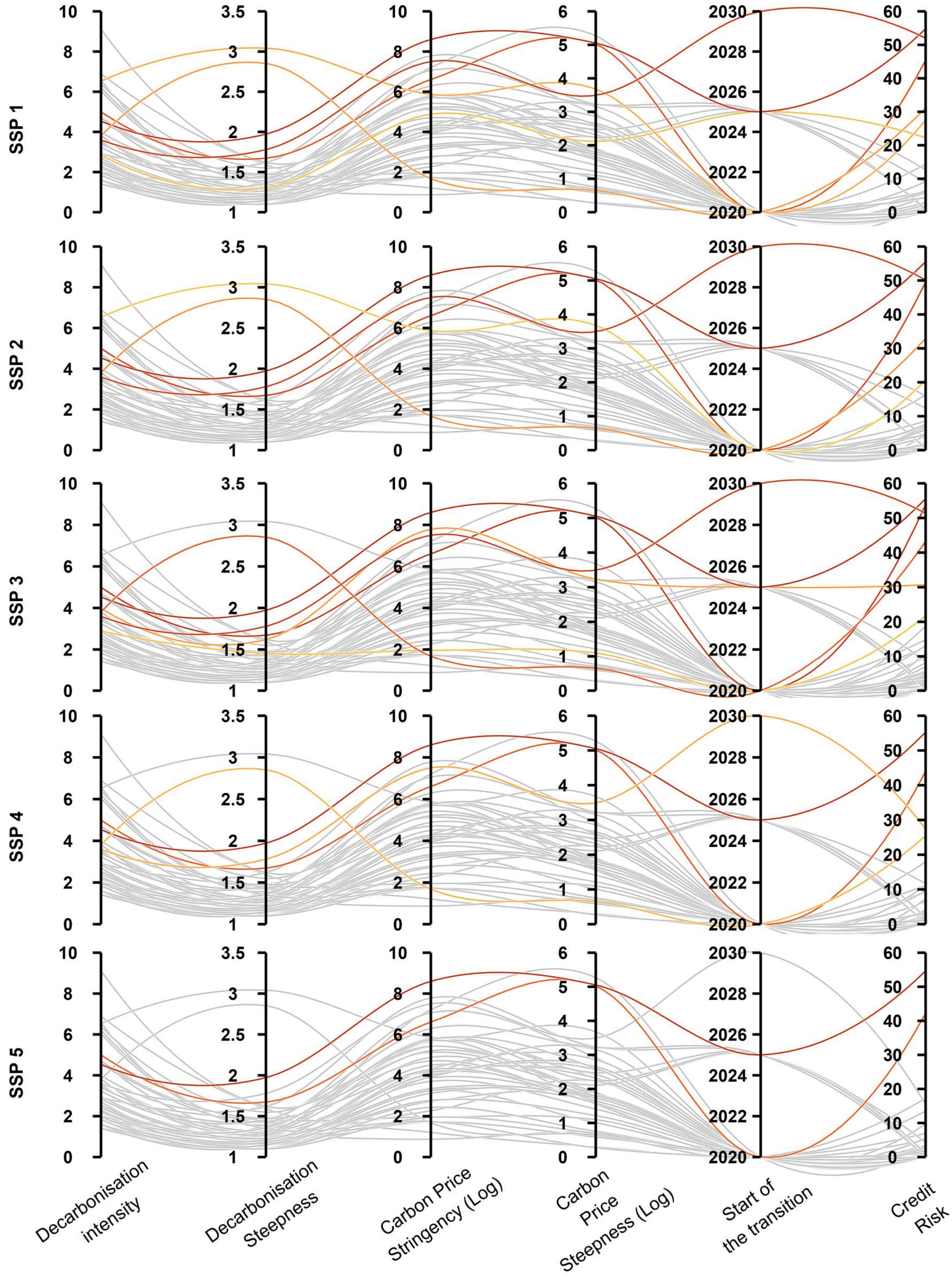

Figure 11: Mapping between credit risks and scenario characteristics. Each line joins a combination of scenario characteristics with the value of the credit risk indicator, which shows on the far-right axis. Colors indicate credit risks, with only scenarios above the 20% threshold highlghted.

delayed action can have very adverse consequences, while in SSP2 and SSP5, they are lower. It flows from the interplay between carbon intensity reduction and growth, which, in turn, affects the relative frailness of the Challenger and the Incumbent sector.

Conversely, in SSP1 and SSP2, both carbon intensity reduction and growth dynamics penalise the Challenger sector, resulting in greater fragility. Furthermore, as sketched above, market risk is higher for 2025 delayed-action scenarios in SSP1. Hence, higher credit risk flows partly from the amplification mechanism flowing from NBFI leverage. For SSP3, shallow growth hampers Incumbents and Challengers by preventing them from enjoying multiplier effects. This interpretation is comforted by Figure 8, which clearly shows that Delayed-Action scenarios feature amongst those with the highest firm risks, especially for SSP1 to 3. This result highlights the importance of the Challenger sector in driving shocks to Banks. More precisely, they further highlight that Challenger risks need not be as high as Incumbent risks to trigger disturbances: due to its fast development, a higher default probability will result in more NPLs in absolute than the Incumbent sector, whose size in Banks' portfolio decreases through time (see Appendix C.2.). Because this sector expands and represents, in the longer run, Banks' main loan outlet, a higher Challenger fragility can exacerbate the risks posed by sunset industries. Thus, some SSP-scenario combinations give rise to "green bubble" behaviours (Nikolaidi 2017).

5.2.2 Timing

To complement this analysis in terms of magnitude, it is worth considering the timing of financial risks to characterise the transition risk profile of our scenarios better. As highlighted in Daumas (2022) (Chapter 2), transition risks can extend beyond the short run. For brevity, we only focus here on the indicator showing the apex of credit and market risks and postpone the discussion of the length of high financial risk periods to Appendix C.1.

Figure 12 shows the period of maximum market risk (x-axis) and credit risk (y-axis) in the same locus. To give a sense of how timing relates to the characteristics of mitigation pathways, we display results in two separate panels, one relating timing indicators to intensity measures and the other to steepness measures.

Results show a wide gradient of occurrences, ranging from early years (2021) to late periods (as late as 2050 for credit risks). Thus, our results clearly show the existence of long-run financial transition risks across scenarios. Furthermore, compared to results in Daumas (2022) (Chapter 2), credit risk for Banks can also emerge in the long run. It is especially the case for delayed-action scenarios. In addition, results exhibit a rough positive correlation between the two indicators. Given the interaction between NBFI leverage and Banks' capital adequacy ratio, it was expected because of the transition process.

Furthermore, the patterns of timing can meaningfully be attributed to the characteristics of our best representatives. Three cases can be highlighted.

For a few scenarios, credit risks occur earlier than market risks, around 2021, and with the market risk apex emerging in the medium to long run. It mostly concerns scenarios with low carbon prices overall, medium to high ambitions and low steepness indicators. It suggests that progressive decabornisation and slowly increasing carbon price schedules give more easily rise to long-run market risk. This feature arises because asset losses in these scenarios are postponed relatively to other cases. The carbon price burden increases slowly and is high relatively late, while decarbonisation is equally slow, leading to late losses in market shares for the Incumbent. This configuration is very close to the one encountered by Daumas (2022) (Chapter 2), whereby Banks' NBFI risk grows in the medium to long run with Banks being able to navigate it. The scenarios with high ambition and medium-high carbon prices exhibit NBFI risks emerging around 2035, suggesting that the conjunction of these two factors accelerates the emergence of NBFI risks due to earlier and more important losses on dividend proceeds and equity prices.

Other scenarios exhibit credit risks occurring later than market risks. Most of these scenarios feature amongst the highest carbon price paths, which are often associated

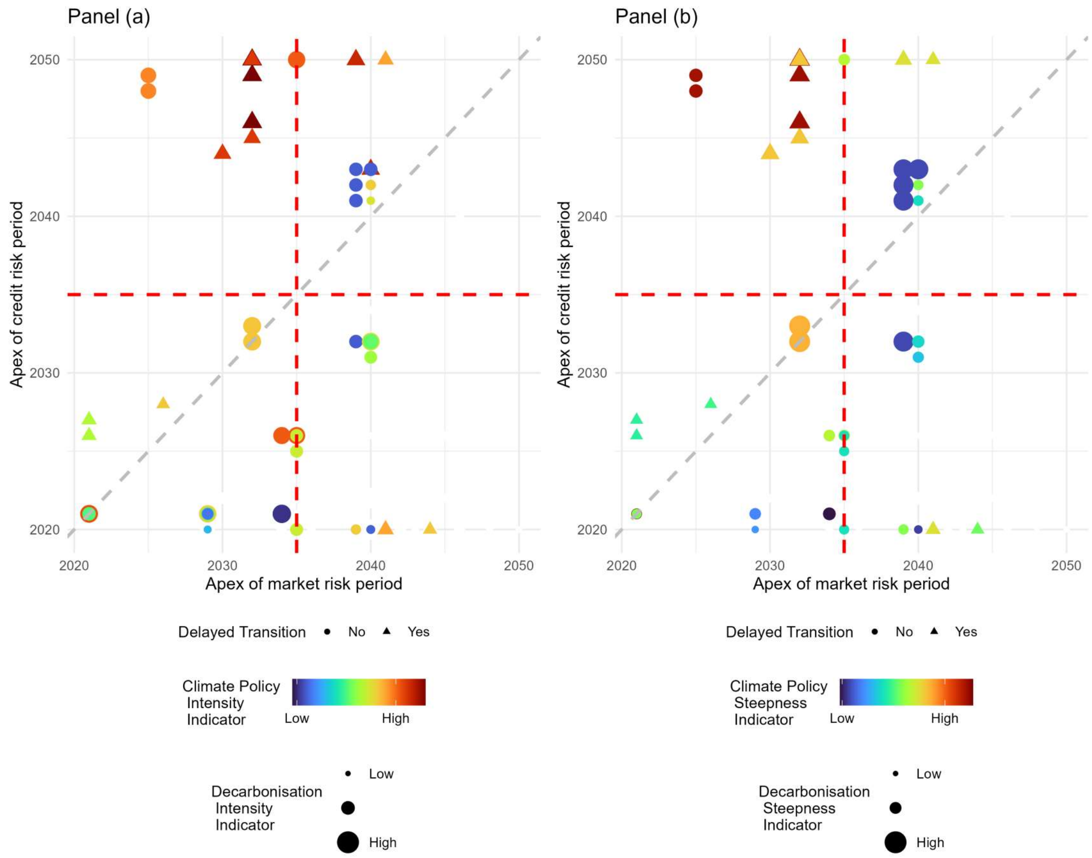

Figure 12: Timing of financial risk events. In both figure, on the x-axis the year of market risk apex, on the y-axis the apex year of market risk. In Panel (a), these two values are associated with intensity indicators. Color indicates Climate Policy Stringency and Size indicates Decarbonisation Steepness. In Panel (b), market and credit risk apexes are associated with steepness indicators. Color indicates Climate Policy Steepness and Size indicates Decarbonisation Steepness. In both Panels, Shape indicates whether the transition starts after 2025 (Delayed Action). Only scenarios with a credit risk ρ_C above 20% or a market risk ρ_M above 7.5% are displayed.

with low or medium decarbonisation targets (Figure 11). It shows that scenarios with low climate policy efficiency affect credit risk in the longer run more than in the short run. It is because the tax burden on Incumbents becomes gradually unsustainable for this sector, weighing on its repayment abilities in the long run. In contrast, NBFIs can benefit from the development of the Challenger, which pays enough dividends to avoid disturbances in the long run.

Finally, around a third of our scenarios come very close to the 45° line. For this group, credit and market risks occur roughly simultaneously. It suggests that within-finance interactions are at play. It mostly occurs for scenarios with high decarbonisation steepness, regardless of the carbon price schedule. Hence, amplification from within the financial sector emerges mostly in case of strong decarbonisation shocks at some point in time.

These results illustrate the importance of mitigation pathways's characteristics on the qualitative profile of financial risk and on the time distribution of financial shocks, with possibly very large differences across our best representatives.

6 Conclusion and discussion

6.1 Summary and takeaways

The results above bear some takeaways. First, there is no strict relationship between the ambition of climate policy and the stringency of climate policy on the one hand and the transition risk content of scenarios on the other. Many climate-ambitious scenarios do not pose very high transition risks, even with relatively high carbon prices. This perspective is reassuring regarding the low-carbon transition. High climate targets with medium to medium-high carbon prices are achievable without threatening financial institutions.

Yet, the population of scenarios with high financial risks is far from anecdotal, with 40% of our best representatives crossing one of our high-risk boundaries. Like in Daumas (2022) (Chapter 2), Non-Bank Financial Institutions seem more at risk than Banks across all scenarios. The extent of market transition risks seems higher. In particular, ambitious scenarios are only achievable by reaching a 7% peak NBFI default probability, a high number by historical standards. It calls for caution in handling these institutions along transition pathways. However, in the riskiest scenarios, large shocks are short-lived and confined to the immediate aftermath of the start of the transition. Banks seem more sheltered, although they can be direly affected in some high-risk scenarios.

We find first some dependence on underlying macroeconomic and carbon intensity reduction assumptions as embodied in SSPs. Low-growth assumptions entail higher risks. However, growth assumptions interact strongly with assumptions on carbon intensity reductions. Indeed, scenarios with stronger autonomous carbon intensity improvements are riskier. This pattern is due to our Challenger-Incumbent structure. Within the boundaries of our model, more significant carbon intensity reductions favour the Incumbent sector at the expense of the Challenger sector. The Challenger sector will have a more fragile financial position because it will snatch fewer market shares and benefit from lesser cash flows and asset stranding will be lower in the Incumbent sector. In some scenarios, this high fragility ripples off to the financial sector, pointing at possible “green bubble” dynamics. More precisely, the model shows that the structure of competition between Incumbents and Challengers matters: a relative advantage to the Incumbent sector can bear substantial risks.

Beyond variations across SSP assumptions, transition risks are, in this study, primarily driven by the shape of emission reduction and carbon price schedules.

First, the pace of emission reduction matters. Scenarios featuring very sharp period-to-period emission reductions from some point onward are among the highest-risk profiles. It is notably valid for market risks, which depend heavily on changes in market shares between the Incumbent and the Challenger sectors. Brisk changes introduce sudden asset revaluations that weigh on NBFI’s default probabilities. Our results thus qualify the need for a progressive deployment of low-carbon technologies along the NGFS’s “orderly” scenario category (NGFS 2022). The study instead shows that the new low-carbon economy should deploy at a workable but sustained rate: too progressive a transformation postponing high efforts in the medium to long run features high risks.

However, the highest-risk scenarios for market and credit risk feature high and rapidly increasing carbon prices with relatively low and slow decarbonisation processes. Scenarios with high or very high carbon prices for mid-range climate ambition and relatively slow decarbonisation processes imply that the carbon tax burden on Incumbents is high and stays long, increasing their fragility.

In the end, the most significant driver of financial transition risks in this study is the efficiency of climate policies in achieving given targets. These results highlight the importance of accounting for the uncertainties surrounding the precise unravelling of the low-carbon transition and the degree of policy pressure put on sunset industries necessary to achieve climate targets.

Regarding the pace of low-carbon technology deployment – and associated structural change, a definite cause of worry is that it is only partly a policy variable. Our results show that it is better to be relatively ambitious in the short run and avoid postponing significant adjustments – even if the transition starts early. However, the speedy development of low-carbon technology can flow from market mechanisms. As evidenced by previous technological shifts, technologies can autonomously develop following an S-shape curve, possibly very sharp, that may put Incumbents in difficulty (Grubb, Drummond, and Hughes 2020).

Second, regarding climate policy, our results highlight the risks associated with the uncertainties related to the efficiency of climate policies. Indeed, although the international community agreed on an adequate price of around US$100 per ton of carbon (Stiglitz and Stern 2017), the possibility of catastrophic climate change effects may bring the range of optimal carbon prices much higher (Kemp et al. 2022). As evidenced by Green (2021), carbon prices have, most of the time, had a modest effect on emission reductions. Conversely, Tvinnereim and Mehling (2018) highlighted that carbon prices have failed to trigger deep decarbonisation efforts. Finally, even relatively higher carbon prices in some jurisdictions have failed in cancelling high-carbon projects, which are still in the pipeline (Kühne et al. 2022). Although the recent increases in the EU exchange trading system have brought hope in a strong reaction of concerned industries, whether they will actually carry out large-scale their decarbonisation efforts in the longer run is still pending. As a result, this study highlights the need for strong macro-prudential policies to best hedge possibly inefficient climate policies.

6.2 Limits and further work

This work, nonetheless, comes with some caveats.

First, although we allow for capital conversion on the part of the Incumbent, it does not invest directly in low-carbon capital. As a result, the transition risk impacts on Incumbents should be taken as an upper bound. On the other hand, our assumptions on autonomous carbon intensity improvements provide Incumbents with another lever of decarbonisation. The model's behaviour with these assumptions offers us a preliminary grasp of how greenfield low-carbon investment from the Incumbents would play out. Indeed, as we saw, favouring the Incumbent sector makes the Challenger sector more fragile. As a result, allowing for a more active role for the Incumbent would push the model towards "green bubble" dynamics, whereby the birth of new industries is eventually thwarted by the Incumbent, with possible implications for financial instability.

Then, how we modelled SSPs in the model led to counter-intuitive results, notably how we dealt with carbon intensity improvements. Due to this approach, SSP1, while the least risky of all SSPs *ex-ante*, becomes one of the riskiest. Conversely, SSP5 is the least risky of all – also because of its very optimistic growth assumptions. A way to bypass this caveat would have been to solve the model for each SSP, like any other scenario. However, it would have required making additional assumptions on the relative behaviour of carbon intensity improvements (or worsening) and the penetration of low-carbon technology through the Challenger. If it would have been relatively straightforward for SSP1 and SSP5, the three other SSPs would have been much less determined. Our choice thus obeyed a constraint of clarity and simplicity.

Finally, as mentioned above, the "carbon prices" we impose upon the model should be taken cautiously. In particular, the POLES-ENGAGE modelling framework generated the riskiest scenarios we obtained. POLES-ENGAGE is a bottom-up integrated assessment model solved in partial equilibrium. As a result, it does not account for the macroeconomic and welfare effects. This feature potentially leads it to yield prohibitively high carbon prices in generating its solutions. Hence, although these extreme scenarios illustrate the relevance of carbon pricing in driving potential crises, applying POLES-generated carbon prices is maximalist and represents an extreme-tail course of events.

Further work thus includes refining the modelling framework in various directions, along with those put forward in Daumas (2022) (Chapter 2): increasing financial sector heterogeneity and implementing a degree of geographical disaggregation. For this article, more specifically, allowing for greater Incumbent adaptability, for instance, by allowing greenfield investment in low-carbon technologies, would also allow us to be more precise in disentangling Challenger and Incumbent-related risks. It would require an explicit representation of competition across both sectors. More generally, adopting a more technology-rich approach, with a greater disaggregation of industries and energy types, could allow for a finer-grain picture of transition risks associated with sunset and sunrise industries, our current Challenger-Incumbent distinction being quite stylised. Furthermore, FASM-ID is currently geared to study transition financial risks associated with completed decarbonisation processes (see Chapter 2). Allowing for failed transition, and therefore more comprehensive interactions between the financial sector and transition dynamics (see Battiston, Monasterolo, Riahi, et al. 2020; Gourdel, Monasterolo, and Gallagher 2023), could allow us to determine more precisely which scenarios within our population of best representatives are truly "unfeasible" from the standpoint of financial instability.

Finally, we confined ourselves to the scenarios featured in the IPCC database. Although they represent a large population of projections meant to map best the uncertainties related to the low-carbon transition, they do not span the entirety of possible transition pathways and leave aside many dimensions relevant to financial risks. For instance, very low-growth or degrowth scenarios are currently not in the set studied by the IPCC – the lowest baseline growth assumptions are slightly below 2% per year on average in SSP3. Given the importance of growth assumptions in driving some of our results, studying transitions towards a low-growth or a steady-state economy (as in T. Jackson and Victor (2015) or P. Jacques et al. (2023)) could be a valuable addition to studying transition risks. Finally, the macroeconomic assumptions embodied in SSPs could be augmented in various directions, for instance, with complementary climate or macro-financial policies that may alleviate transition risks.

This third chapter closes the first movement of this dissertation by providing a direct answer to its research question. By applying FASM-ID to a wide array of scenario representatives, this chapter directly studied the transition risk properties of canonical mitigation pathways provided by the IPCC. It further built on the latter's methodology by offering a treatment of assumptions embodied in the Shared Socioeconomic Pathways. As highlighted, however, this work is limited by scenario and modelling assumptions. The two following chapters aim to dig more into this latter direction by focusing on two avenues highlighted in Chapter 1. Chapter 4 proposes a novel way to model expectations, which could be adapted to transition-relevant scenarios within FASM-ID in later works. Chapter 5 digs more into the details of portfolio choices away or into carbon-intensive companies at the investor level. Its goal will be to pinpoint what kind of investors have been most prone to increase their investments in high-carbon companies.

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Appendices

A. Scenario references

Table A1: Best representative – References

ID	Model	Scenario	Reference
1	POLES ENGAGE	EN_NPi2020_600	Bertram, Riahi, et al. (2021)
2	MESSAGEix-GLOBIOM_1.2	COV_SelfReliance_550	Kikstra et al. (2021)
3	WITCH 5.0	EN_NPi2020_1200f	Bertram, Riahi, et al. (2021)
4	POLES EMF33	EMF33_Med2C_nofuel	Vinichenko, Cherp, and Jewell (2021)
5	MESSAGEix-GLOBIOM_1.1	EN_NPi2020_1000f_COV	Bertram, Riahi, et al. (2021)
6	REMIND-MAgPIE 2.1-4.2	EN_NPi2020_300f	Bertram, Riahi, et al. (2021)
7	AIM/CGE 2.1	CD-LINKS_NPi2020_400	Bertram, Riahi, et al. (2021)
8	POLES ENGAGE	EN_NPi2020_400f	Bertram, Riahi, et al. (2021)
9	POLES ENGAGE	EN_INDCi2030_700f	Bertram, Riahi, et al. (2021)
10	REMIND-MAgPIE 1.7-3.0	PEP_2C_red_netzero	Bertram, Riahi, et al. (2021)
11	IMAGE 3.0	EN_INDCi2030_1000	Bertram, Riahi, et al. (2021)
12	REMIND 2.1	CEMICS_opt_2C	Strefler et al. (2021)
13	MESSAGEix-GLOBIOM_1.1	EN_INDCi2030_1000f	Bertram, Riahi, et al. (2021)
14	POLES ENGAGE	EN_NPi2020_900	Bertram, Riahi, et al. (2021)
15	REMIND-Transport 2.1	Transport_Budg1100_Conv	Rottoli et al. (2021)
16	MESSAGEix-GLOBIOM_1.1	EN_NPi2020_600f_DR4p	Riahi, Bertram, et al. (2021)
17	REMIND 2.1	TechCost-SSP2-B1100-windH	Giannousakis et al. (2020)
18	POLES GECO2019	CO_2Deg2020	Morris et al. (2021)
19	POLES ENGAGE	EN_NPi2020_1000_COV	Bertram, Riahi, et al. (2021)
20	EPPA 6	2CNow_Gradual	Morris et al. (2021)
21	GEM-E3_V2021	EN_NPi2020_1400f	Bertram, Riahi, et al. (2021)
22	IMAGE 3.0	EN_NPi2020_1000	Bertram, Riahi, et al. (2021)
23	COFFEE 1.1	EN_INDCi2030_1000_NDCp	Bertram, Riahi, et al. (2021)
24	TIAM-ECN 1.1	EN_NPi2020_1200f	Bertram, Riahi, et al. (2021)
25	TIAM-ECN 1.1	EN_NPi2020_1600	Bertram, Riahi, et al. (2021)
26	COFFEE 1.1	EN_NPi2020_1200	Bertram, Riahi, et al. (2021)
27	WITCH 5.0	EN_NPi2020_700f	Bertram, Riahi, et al. (2021)
28	MESSAGEix-GLOBIOM_1.2	COV_Restore_1000	Bertram, Riahi, et al. (2021)
29	POLES ENGAGE	EN_INDCi2030_1000f_COV_NDCp	Bertram, Riahi, et al. (2021)
30	GEM-E3_V2021	EN_INDCi2030_1000	Bertram, Riahi, et al. (2021)
31	POLES ENGAGE	EN_INDCi2030_1200	Bertram, Riahi, et al. (2021)
32	TIAM-ECN 1.1	EN_INDCi2030_1000f	Bertram, Riahi, et al. (2021)
33	MESSAGEix-GLOBIOM_1.1	EN_INDCi2030_1200f_COV	Bertram, Riahi, et al. (2021)
34	COFFEE 1.1	EN_INDCi2030_600f	Bertram, Riahi, et al. (2021)
35	POLES ENGAGE	EN_INDCi2030_300f	Bertram, Riahi, et al. (2021)
36	REMIND-MAgPIE 2.1-4.2	EN_INDCi2030_600_COV_NDCp	Bertram, Riahi, et al. (2021)
37	COFFEE 1.1	EN_INDCi2030_600	Bertram, Riahi, et al. (2021)
38	POLES ENGAGE	EN_INDCi2030_900f	Bertram, Riahi, et al. (2021)
39	REMIND-MAgPIE 2.1-4.2	EN_INDCi2030_600f_COV	Bertram, Riahi, et al. (2021)
40	MESSAGEix-GLOBIOM_1.1	EN_INDCi2030_600f_COV	Bertram, Riahi, et al. (2021)
41	MESSAGEix-GLOBIOM_1.1	EN_INDCi2030_700f_COV	Bertram, Riahi, et al. (2021)
42	POLES GECO2019	CO_Bridge_notax	COMMIT Database
43	TIAM-ECN 1.1	EN_NPi2020_900f	Bertram, Riahi, et al. (2021)
44	COFFEE 1.1	EN_NPi2020_500f	Bertram, Riahi, et al. (2021)
45	MESSAGEix-GLOBIOM_1.1	EN_NPi2020_1400f_COV	Bertram, Riahi, et al. (2021)
46	MESSAGEix-GLOBIOM_GEI 1.0	SSP2_noint_lc_50	Guo et al. (2021)
47	COFFEE 1.1	CO_2Deg2020	COMMIT Database
48	IMAGE 3.0	CO_Bridge	COMMIT Database
49	REMIND-MAgPIE 2.1-4.2	EN_NPi2020_1200	Bertram, Riahi, et al. (2021)
50	POLES ENGAGE	EN_NPi2020_1200	Bertram, Riahi, et al. (2021)

B. Calibration details

The calibration method is the same as in Chapter 2, to the difference that stylised facts and starting values are targeted over a no-policy steady-state and not a baseline scenario involving some degree of decarbonisation. We target the same starting values and stylised facts as in Chapter 2. Parameter values are the same as in Chapter 2, except for the moving calibration parameters presented in Chapter 2. The latter differ across SSPs to yield the desired macroeconomic properties. Finally, given differences in growth rate, the number of iterations necessary to reach target starting values could also change across SSPs.

B.1. Sensitivity ranges

We display again in Table B.1.1 Table D.1 of Chapter 2 reproducing the sensitivity ranges for the parameters involved in sensitivity calibrations. Note the absence of the carbon improvement coefficient β_e, whose effect is neutralised in the model due to our assumption of autonomous carbon intensity improvements.

B.2. SSP-specific parameters

Like in Chapter 2, the reference calibrations are generated by moving the parameter ruling the response of consumption, γ_C and the parameter ruling trend inflation $\nu_{w,2}$. Table B.2.1

C. Complementary results

C.1. Length of high financial risk periods

Another aspect of timing is the length of higher-risk periods. It complements the apex date metric by providing a sense of how protracted tension periods are and can give a sense of whether credit and market risk periods overlap. We report this result in Figure C.1.1, which shows the duration of market and credit risk shocks in the same locus, with the same two Panels as in Figure C.3.2.

Table B.1.1: Sensitivity parameters and corresponding ranges

Parameter	Reference values	Range
$\bar{\mu}$	0.065	[0.0585, 0.0715]
$\bar{lev}$	0.2	[0.14, 0.26]
γ_C	0.073	[0.0657, 0.803]
$\lambda_{i,j},\ i,j \in [\|1,3\|]$	0.06 -0.03 otherwise (Ruled by a single parameter λ_λ with value 0.06, on which the value of the other Tobin coefficients are computed)	[0.048,0.96]
λ^*_{KLC}	3	[2.4,3.9]
λ^*_o	1	[0.7, 1.3]
ν	0.1	[0.07, 0.13]
ν_{w_1}	0.7	[0.63, 0.77]
ν_{w_2}	1.1	[0.088, 1.32]
ν_u	0.04	[0.028, 0.052]
ω_p	0.2	[0.14, 0.26]
r_D	0.005	[0.035, 0.065]
r_{CB}	0.01	[0.007, 0.013]
r_{GB}	0.02	[0.014, 0.026]
σ_{LC}	0.025	[0.1225, 0.5]
σ_{HC}	0.025	[0.1225, 0.5]
σ_{NBFI}	0.025	[0.1225, 0.5]
σ_{lev}	0.025	[0.1225, 0.5]
τ_{Tob} 0.5	[0.25,1]	
φ_1	8.17	[7.96, 8.37]
φ_2	7.925	[7.1325, 8.7175]
ϖ_1	2	[1.8,2.2]
ϖ_2	2	[1.4,2.6]
ϖ_3	6	[4.2,7.8]
ξ_B	0.4	[4.2,7.8]
$\xi Funds_B$	0.1	[0.07, 0.13]
$\xi NBFI$	0.9	[0.81, 0.99]

*Starting value before the learning period of the model

Table B.2.1: SSP-Specific parameters

Variable	SSP1	SSP2	SSP3	SSP4	SSP5	Sensitivity range
γ_C	0.081	0.77	0.063	0.074	0.1	$\pm$10%
$\nu_{w,2}$	0.635	0.66	0.77	0.69	0.49	$\pm$20%

Strikingly, the pattern of the scatter plot is L-shaped, suggesting that, except for a few scenarios, long-lasting tension periods only concern one or the other risk.

Credit risk periods are protracted under low climate-efficiency scenarios, possibly including delayed action. In these best representatives, the carbon price is so high relative to decarbonisation dynamics that it puts the banking sector under pressure for a very long time due to increased default probabilities of Incumbents over a long period. These dynamics also emerge under high decarbonisation stringency, confirming that strong decarbonisation shocks can ripple off to the long run.

By contrast, long market risk periods emerge under scenarios with more progressive decarbonisation and climate policy schedules while being relatively ambitious. Hence, a sustained but progressive pressure can give rise to longer-lasting fragility periods for NBFIs.

Scenarios in which both market and credit risk periods are protracted are all delayed action scenarios with very stringent characteristics. It suggests that the shock of delayed action is high enough to create a long-lasting period of financial fragility.

A sizeable set of scenarios exhibits short-lived financial risks for both indicators with similar characteristics to those with long-run market risks. They differ, however, in featuring either delayed action or low climate ambitions. It suggests that these two characteristics shorten the length of market risk periods.

C.2. Timing results for medium-range financial risks

We then display complementary results about the timing of financial risks for medium-risk profiles. To define such profiles, we isolate scenarios with a credit risk between 10 and 20% and a market risk between 5 and 7.5% and exclude from this selection the SSP-scenario pairs studied in Figures 12 and C.1.1. In that respect, some SSP-scenario pairs discussed above could appear in this Appendix as well because they exhibit smaller risks than their counterpart.

We first display results on the timing of both types of risk. Given our many scenarios, we restrict ourselves to a brief description of the results.

Strikingly, the scenarios with lower financial risks exhibit distinct patterns from those studied in Section 5. In most cases, the high market risk period emerges in the

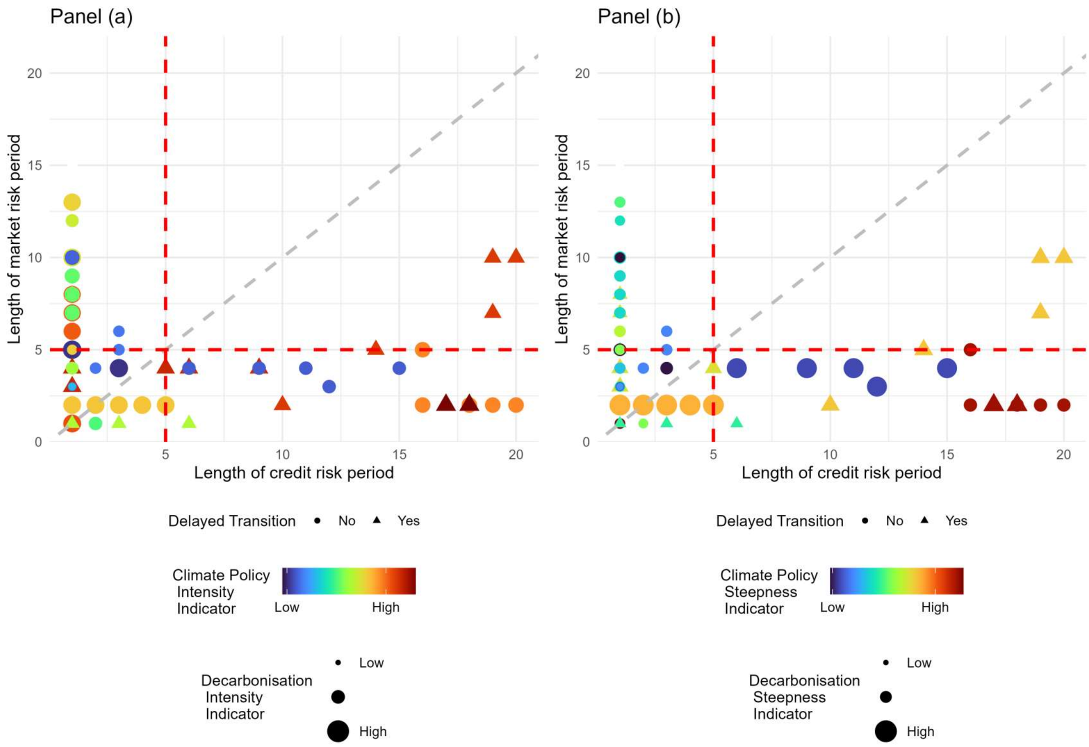

Figure C.1.1: Length of financial risk periods. In both figure, on the x-axis the year of market risk apex, on the y-axis the length of the high credit risk period.In Panel (a), these two values are associated with intensity indicators. Color indicates Climate Policy Stringency and Size indicates Decarbonisation Steepness. In Panel (b), market and credit risk apexes are associated with steepness indicators. Color indicates Climate Policy Steepness and Size indicates Decarbonisation Steepness. In both Panels, Shape indicates whether the transition starts after 2025 (Delayed Action). Only scenarios with a credit risk ρ_C above 20% or a market risk ρ_M above 7.5% are displayed.

medium to long run after the high credit risk period. These patterns align with those found in Daumas (2022) (Chapter 2), whereby a wave of high NBFI risk emerged in the medium to long run when the price of Incumbent equity starts decreasing sufficiently. Most scenarios exhibit a market risk apex in the short-medium run, around 2028. Similarities in apex dates across some scenario groups are primarily due to similar turning points in transition dynamics across scenarios (see Figure 6). Most of these scenarios exhibit a low decarbonisation steepness and low carbon prices, suggesting that a critical factor for the emergence of short-medium-run market risk is the progressive development of low-carbon technologies with relatively efficient climate policies. Higher carbon prices characterise scenarios with later market risk apex. It highlights that relatively less efficient climate policies postpone market risks in the longer run.

However, compared to Daumas (2022) (Chapter 2), credit risk troughs can emerge relatively late, sometimes beyond 2030, even in scenarios that do not assume delayed action. Scenarios with late credit-risk troughs are of several kinds. First, these scenarios with high decarbonisation intensity likely bring the Incumbent sector close to extinction, triggering some financial disturbances. Second, they include scenarios with high long-run carbon prices and sluggish transitions, confirming our result on the relative efficiency of climate policy.

We move to Figure C.2.2, the equivalent of Figure C.1.1 showing the length of high-risk periods around the apex for medium-range risk scenarios.

Again, patterns are different from those prevailing under high-risk scenarios. First, the length of credit risk events is much smaller, rarely above five years. It suggests that in medium-risk configurations, credit risks mainly consist of transitory shocks that Banks eventually absorb.

By contrast, market risk periods can be more protracted. Some scenarios remain within the boundaries of Figure C.1.1, but others exhibit periods ranging between ten and fifteen years, three times those prevailing under high-risk scenarios. Longer-lasting market risk scenarios mostly feature medium-range values for most of our *ex-ante* indicators, highlighting that sustained policy pressure, with relative efficiency, leads to longer-lasting periods of financial fragility. Consistent with the discussion above, the scenarios showing the longest-lasting fragility periods feature relatively low ambition but with either high carbon prices or steeply increasing schedules. Again, it confirms the detrimental role of relatively less efficient climate policy.

C.3. Fim risk

We then consider another set of complementary results on firm risks. Similarly to the results of Section 5, we first discuss the extent of firm risks for Challengers and

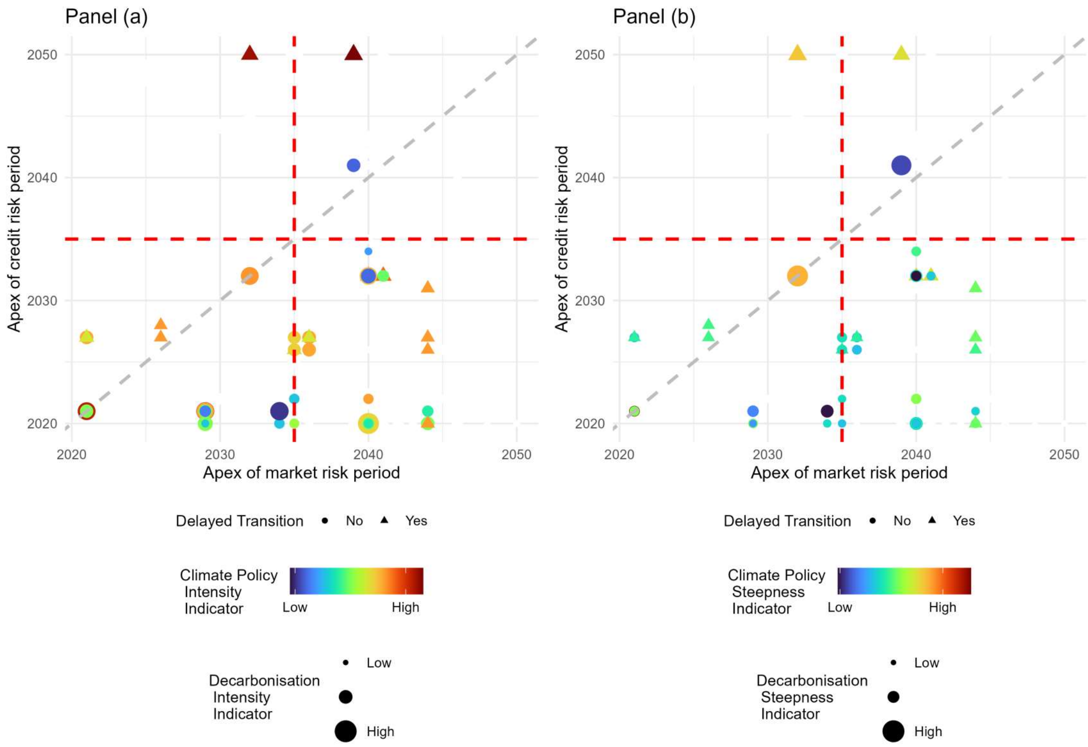

Figure C.2.1: Timing of financial risk events – Medium-range risk. In both panels, on the x-axis the year of credit risk apex, on the y-axis the year of market risk apex. In Panel (a), these two values are associated with intensity indicators. Color indicates Climate Policy Stringency and Size indicates Decarbonisation Steepness. In Panel (b), market and credit risk apexes are associated with steepness indicators. Color indicates Climate Policy Steepness and Size indicates Decarbonisation Steepness. In both Panels, Shape indicates whether the transition starts after 2025 (Delayed Action). Only scenarios with a credit risk ρ_C betwene 10 and 20% or a market risk ρ_M between 5 and 7.5% are displayed.

Incumbents across all scenarios.

Figure C.3.1 displays our magnitude results for the Incumbent. Unsurprisingly, the highest financial risks concentrate in scenarios with the highest carbon prices or the latest transition start. Interestingly, many scenarios with relatively high climate ambitions do not feature high Incumbent risks, which suggests that progressive transitions can be well-managed by this sector. Furthermore, it shows that the most significant determinant of Incumbent risk is the price of carbon, well above technological displacements, which is only problematic for a single scenario. We see a

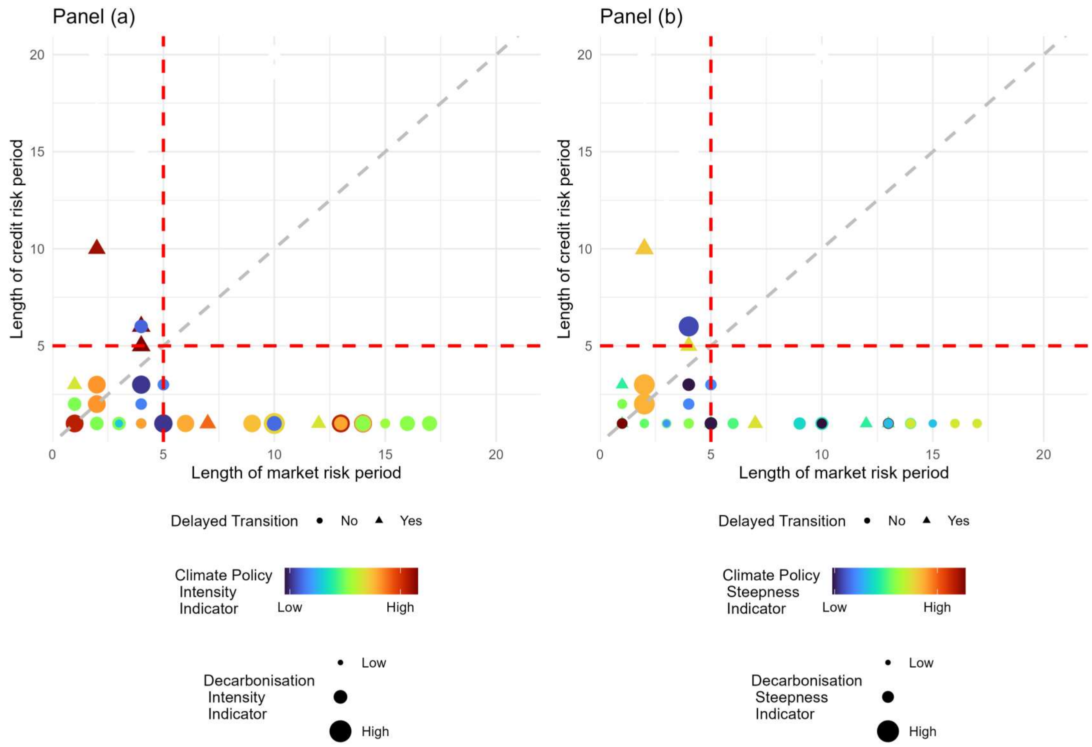

Figure C.2.2: Length of high financial risk periods – Medium Range Risks. In both figure, on the x-axis the year of market risk apex, on the y-axis the apex year of market risk.In Panel (a), these two values are associated with intensity indicators. Color indicates Climate Policy Stringency and Size indicates Decarbonisation Steepness. In Panel (b), market and credit risk apexes are associated with steepness indicators. Color indicates Climate Policy Steepness and Size indicates Decarbonisation Steepness. In both Panels, Shape indicates whether the transition starts after 2025 (Delayed Action). Note: *Only scenarios with a credit risk ρ_C betwene 10 and 20% or a market risk ρ_M between 5 and 7.5% are displayed.*

relatively low variation across SSPs, with SSP5 and SSP1 ranking very high, followed by SSP2 and SSP3. SSP4, by contrast, exhibits comparatively lower Incumbent risk.

Regarding SSP1 and SSP5, results are interesting in showing that carbon intensity improvements do not necessarily shelter the Incumbent sector very much and that growth hypotheses only partially allow it to escape from its financial doldrums. It further confirms that a significant share of financial disturbances, in extreme scenarios, can be attributed to different Challenger dynamics.

SSP2 and SSP4 further illustrate the importance of carbon intensity improvement

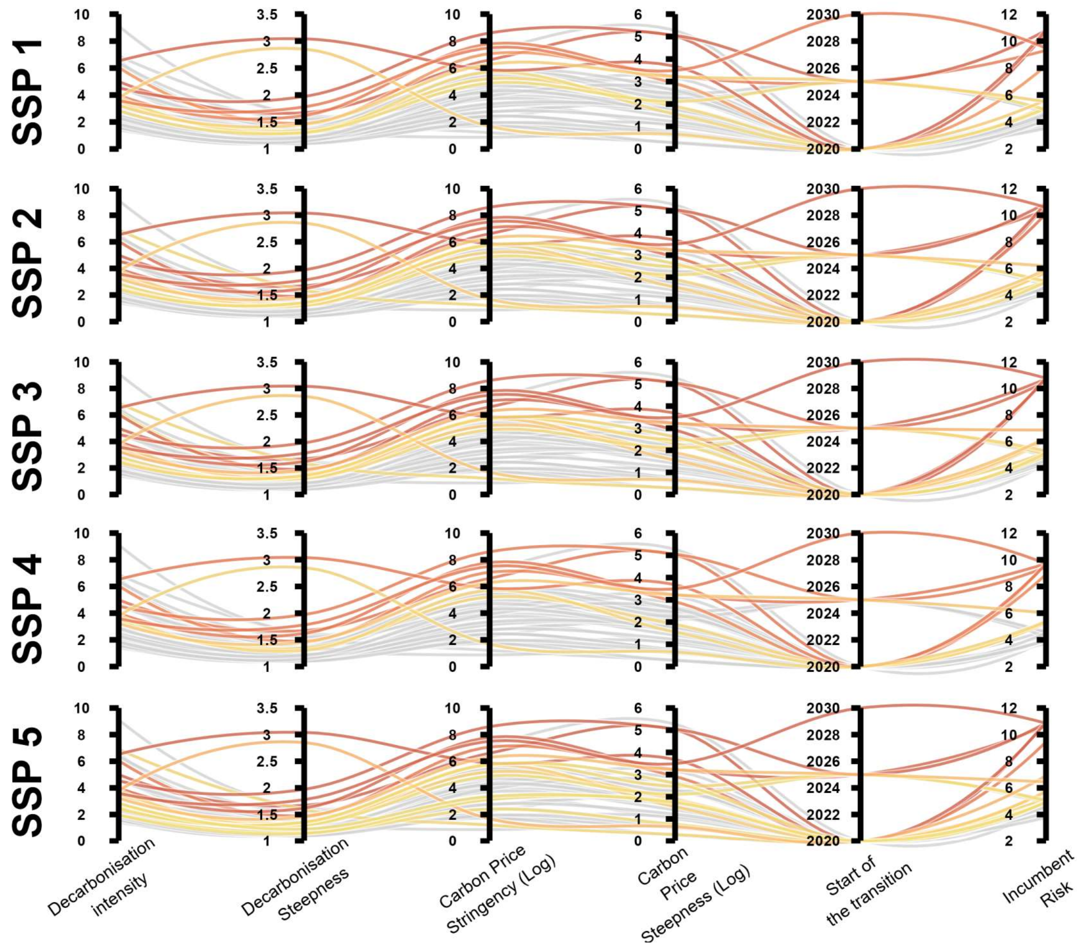

Figure C.3.1: Mapping between firm risk and scenario characteristics for each SSP – Incumbent. Each line joins a combination of scenario characteristics with the value of the outcome of interest, which shows on the far-right axis. Colors indicate Incumbent firm risk. Only combinations with an Incumbent risk above 5% are highlighted.

hypotheses. Being more favourable in SSP4 than in SSP2, they allow the Incumbent sector to partially escape financial turmoil and lower growth, limiting investment needs.

Results finally show the non-linear effects of growth and its interactions with carbon price assumptions. Because of higher growth, investment needs for the Incumbent do not decrease as much as in other instances in SSP1 and SSP5, leading to greater instability overall. In SSP3, low growth impairs the Challenger sector in case of high carbon price, but not in other scenarios.

We now move on to timing indicators for Incumbent risks. For brevity, and given the lesser interactions between Challenger and firm risks, we group all related timing indicators in one graph. That is, we display the time of highest Incumbent risk and the length of the period in the same locus. We only focus on the timing of firm risk events by focusing on the most severe cases, *i.e.*, when the firm risk indicator is above 5%.

The apparent negative correlation between both indicators suggests that, in these cases, the default probability of Incumbent reaches a peak and then decreases more or less late depending on the scenarios, in line with the behaviours shown in Daumas (2022) (Chapter 2). Scenarios with the earliest shocks and the highest shock duration feature high carbon prices or vigorous decarbonisation intensity. Delayed-action scenarios shift the Incumbent risk apex by five to ten years, depending on the transition. Finally, the latest shocks and shortest durations are less stringent scenarios, which postpone financial disturbances to the 2050s.

We now move on to Challenger risk, which shows distinct patterns to Incumbent risk. First, we see a much more significant variation across SSPs. SSP5 and SSP4 exhibit the lowest Challenger risk, while SSP1 shows the highest results. It is consistent with the discussions held in Section 5. Either the Challenger is penalised due to a relative advantage given to the Incumbent thanks to autonomous carbon intensity improvements, or it is affected by lower growth.

Across best representatives, the highest Challenger risks emerge under delayed-action scenarios or those with the highest climate ambition. Investment needs for the Challenger being higher in these scenarios, the sector needs to be improved with a more fragile position due to higher leverage. These effects are exacerbated in scenarios with higher carbon intensity improvements for the Incumbents. Results also highlight a non-linear effect of growth hypotheses. SSP3 (low growth) shows higher Challenger risk, suggesting that a brake on its development can harm its financial position. On the other hand, too high growth, in the presence of carbon intensity improvement,

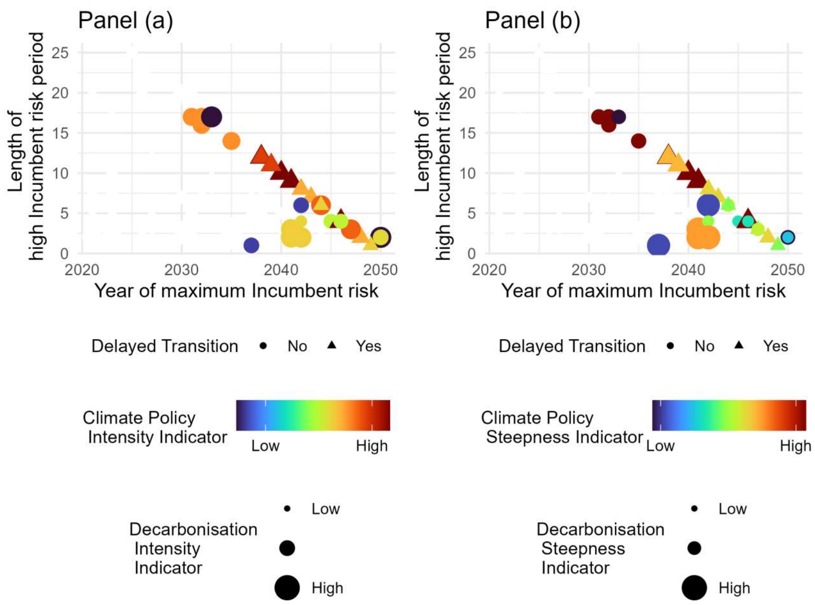

Figure C.3.2: Time structure of firm risk events – Incumbent. In both panels, on the x-axis the year of Challenger risk apex, on the y-axis the length of the high Challenger risk period. In Panel (a), these two values are associated with intensity indicators. Color indicates Climate Policy Stringency and Size indicates Decarbonisation Steepness. In Panel (b), market and credit risk apexes are associated with steepness indicators. Color indicates Climate Policy Steepness and Size indicates Decarbonisation Steepness. In both Panels, Shape indicates whether the transition starts after 2025 (Delayed Action). Only scenarios with a Incumbent risk ρ_{CH} above 5% are displayed

can be highly detrimental. Indeed, in such acase, the Challenger is in charge of most of the investment effort, while its market share does not grow enough for it to cover investment expenses. This development also makes its position more fragile.

Regarding timing, we show results in Figure C.3.4, with the same display as in Figure C.3.2. Very few scenarios exhibit severe Challenger risks. Most show a Challenger risk apex emerging in the early periods of the transition, with a high-risk period lasting for around five years. These scenarios are, overall, the least stringent ones, characterised by some short-run adjustments at the start of the transition. More problematic scenarios feature delayed-action scenarios and scenarios with very high decarbonisation intensity (climate ambition). Again, very high climate targets significantly put much pressure on the challenge sector when carbon intensity improvements

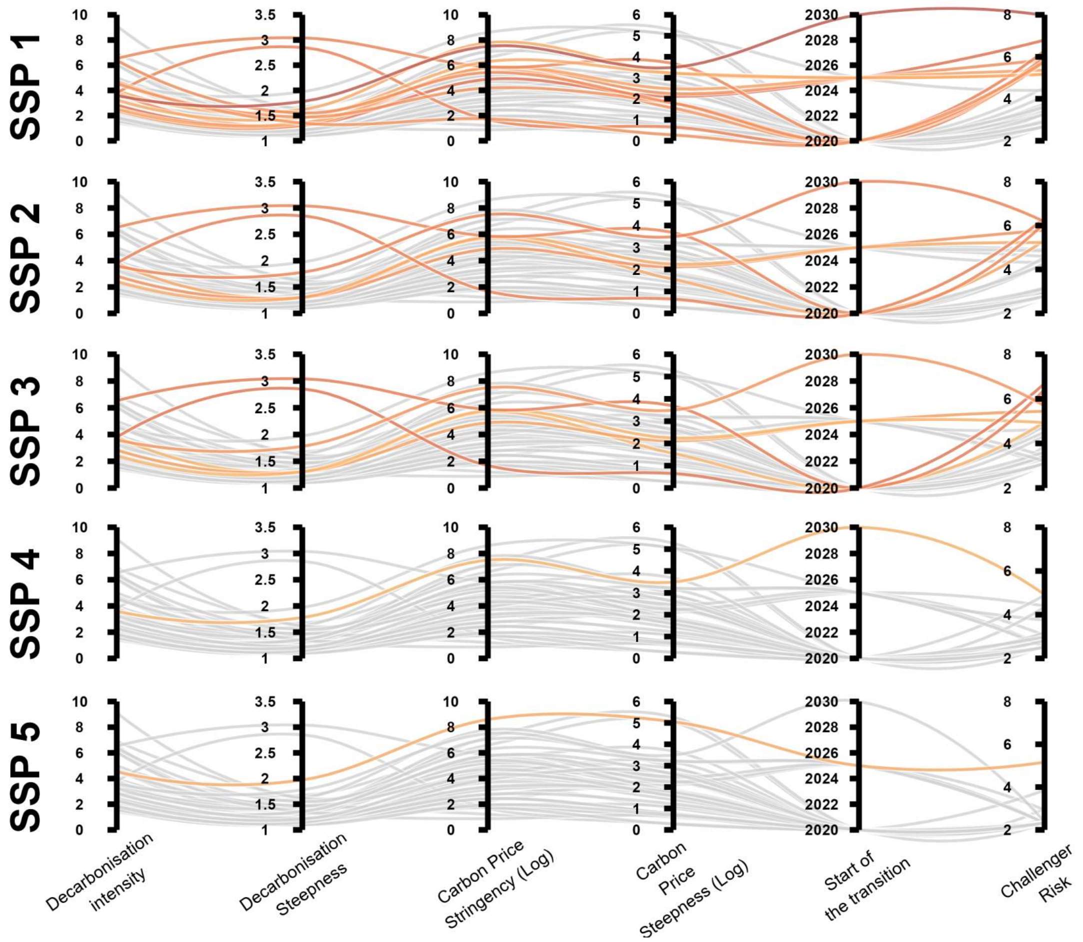

Figure C.3.3: Mapping between firm risk and scenario characteristics for each SSP – Challenger. Each line joins a combination of scenario characteristics with the value of the outcome of interest, which shows on the far-right axis. Colors indicate Challenger firm risk. Only combinations with a Challenger risk above 5% are highlighted.

hamper its development.

D. Sensitivity simulations

In this Appendix, we use our numerous sensitivity calibrations to analyse how outcomes vary for the same Scenario-SSP pair but with different calibrations. For brevity, We also only report results for two outcomes: market and credit risk.

To do so, we first show the dispersion of our outcomes across scenario-SSP pairs. To

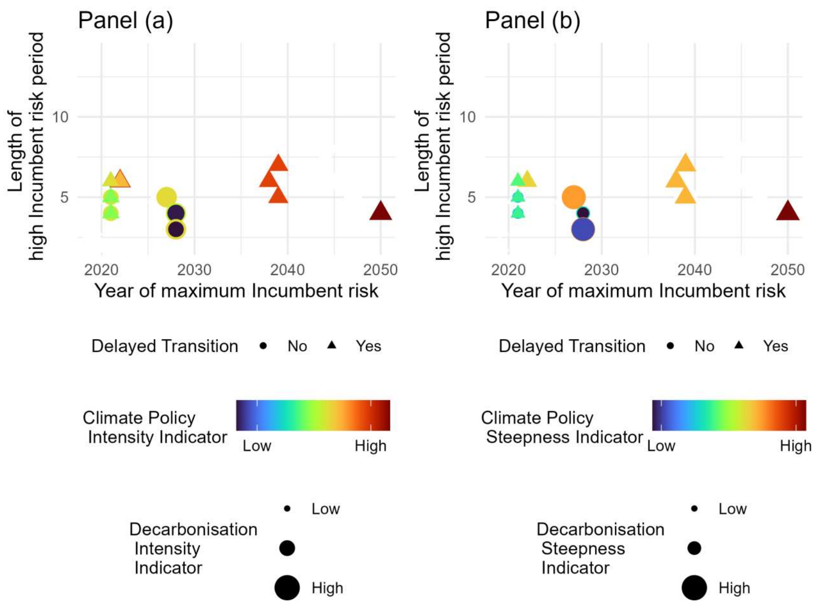

Figure C.3.4: Time structure of firm risk events – Challenger In both panels, on the x-axis the year of Challenger risk apex, on the y-axis the length of the high Challenger risk period. In Panel (a), these two values are associated with intensity indicators. Color indicates Climate Policy Stringency and Size indicates Decarbonisation Steepness. In Panel (b), market and credit risk apexes are associated with steepness indicators. Color indicates Climate Policy Steepness and Size indicates Decarbonisation Steepness. In both Panels, Shape indicates whether the transition starts after 2025 (Delayed Action). Only scenarios with a Challenge risk ρ_{CH} above 5% are displayed

do so, we resort to a variation coefficient defined as follows:

$$C = 100\frac{SD_W(X)}{\bar{X}_W},$$

where the W subscript highlights that we use Winsorised (95%) values for the standard deviation ($SD(X) = \sqrt{V(X)}$, $V(X)$ the variance of X) and the mean ($\bar{X}$). We use this index to provide a normalised measure of our outcomes' dispersion, their means being potentially very different. Here, the (Winsorised) standard deviation is divided by the (Windsorised) mean. Hence, the index must be interpreted as an average deviation from the mean, as a percentage of the mean. Finally, we prolong the sensitivity analysis of Chapter 2 by including the role of SSPs.

D.1. Variance of outcomes

To study the variance of our outcomes, we replace the mean result across sensitivity calibrations presented in Section 5 with the corresponding variance using our parallel coordinate plot template. We first report results for market risk and then for credit risk.

As shown in Figure D.1.1, the variance of our result is very low for market risks for a large swath of scenarios. For SSP4 and 5, no scenario exhibits a market risk indicator with a standard above 40% of the mean. The others *exhibit* relatively higher variances, with some scenarios showing a higher variance due to outliers. These scenarios have the highest *ex-post* and transition risk content. They illustrate that a stronger sensitivity to transition risks also introduces a higher sensitivity to parameter assumptions. Note that these results also hold for the scenarios yielding the highest mean outcome, increasing confidence in our results.

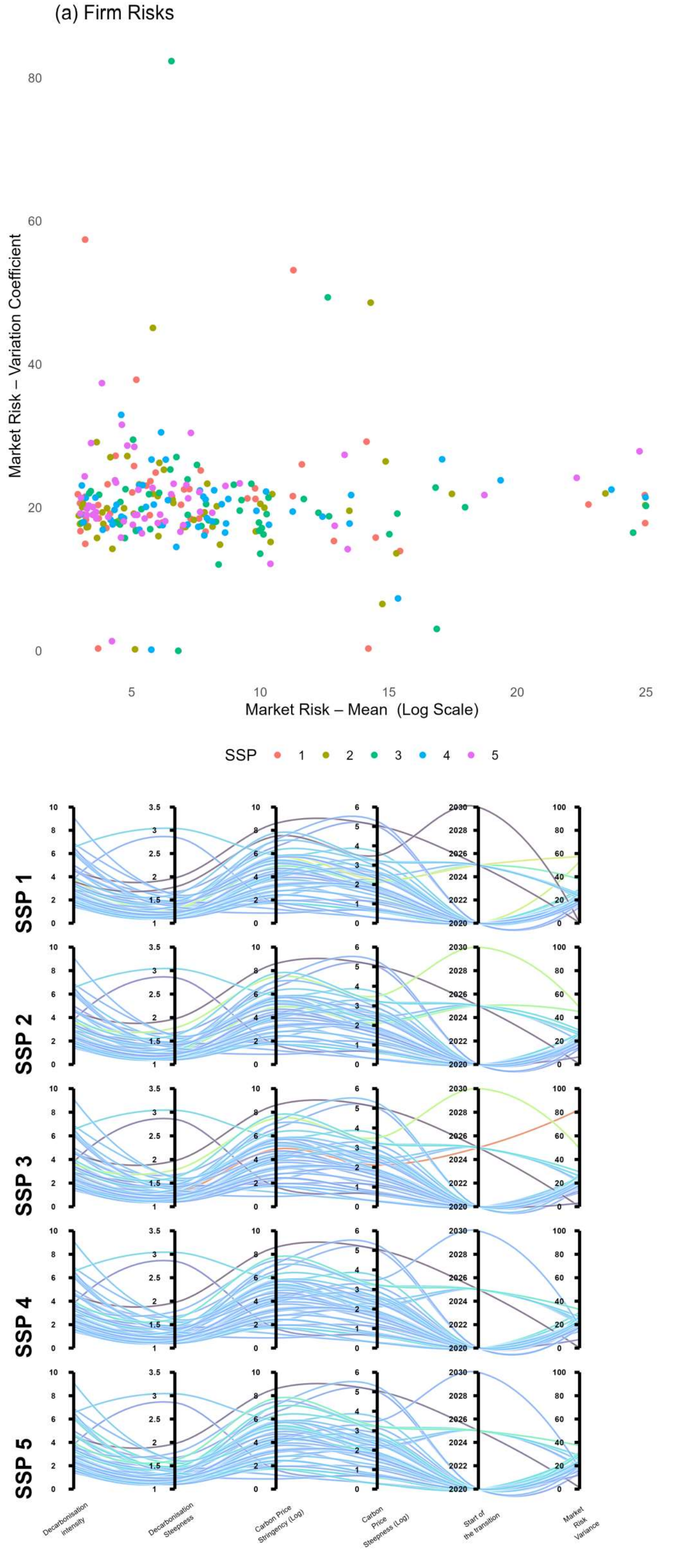

Figure D.1.1: Mapping between market risk variance and scenario characteristics for each SSP. In Panel (a) Each bubble is a scenario, with colors giving the SSP. In Panel (b), the variation coefficient of the outcome is associated with mitigation pathways' characteristics. Each line joins a combination of scenario characteristics with the value of the outcome of interest, which shows on the far-right axis. Colors indicate the variance of the outcome for a given scenario.

Figure D.1.2 shows a distinct picture of credit risk. Overall, deviations can be much higher, reaching values above 1,000%. These high numbers indicate a higher presence of outliers for some SSP-scenario pairs and, therefore, a higher degree of non-linearity between parameter assumptions and credit risk. Overall, scenarios with high variation coefficients are scenarios with low decarbonisation intensity and stringency relative to their climate policy assumptions, except for our highest-ambition scenario. As a result, scenarios with low climate policy efficiency relative to modest climate targets seem more sensitive to calibration assumptions, highlighting the destabilising potential of low-efficiency climate policy.

However, there is very little uncertainty in high-risk scenarios, which suggests that, above a certain threshold, inefficient climate policies are adverse in any state of the world. Finally, regarding SSPs, while SSP1-4 exhibits very similar patterns, with roughly the same population of high-variance scenarios, SSP5 exhibit one scenario with very high variation, highlighting the presence of some outliers. Hence, albeit safer on average, SSP5 scenarios can exhibit high sensitivity to macroeconomic data.

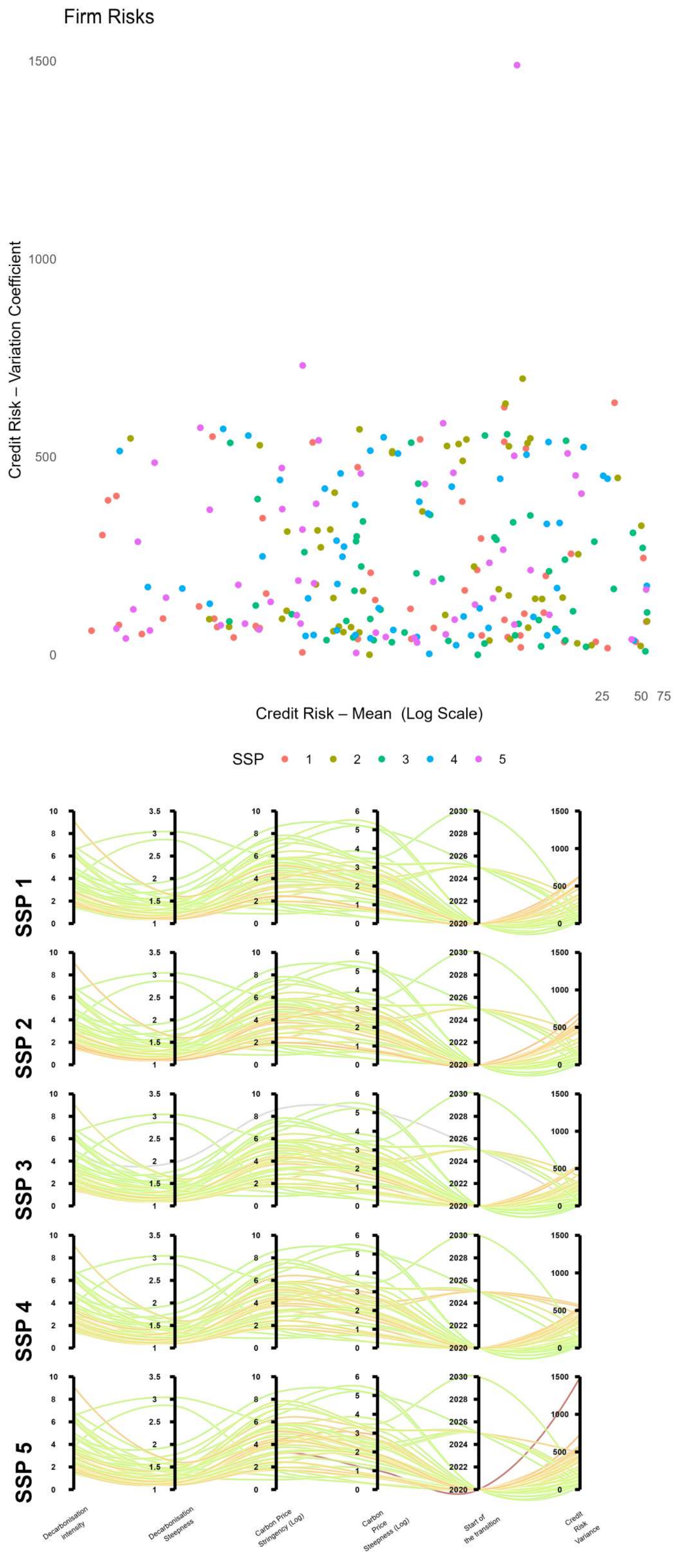

Figure D.1.2: Mapping between credit risk variance and scenario characterisation for each SSP. In Panel (a) Each bubble is a scenario, with colors giving the SSP. In Panel (b), the variation coefficient of the outcome is associated with mitigation pathways' characteristics. Each line joins a combination of scenario characteristics with the value of the outcome of interest, which shows on the far-right axis. Colors indicate the variance of the outcome for a given scenario.

D.2. Sensitivity analysis across SSP-MP pairs

We follow, link in Chapter 2, by regressing our parameters on our two outcomes of interest by selecting the best-fit model with an AIC criterion. To be consistent with the above dispersion measures, we run regressions on Winsorised outcomes at 95%. We report the results in Table D.2.1. Note that for the credit risk outcome ρ_C, the interpretation of the signs should be reversed with respect to Chapter 2, since a higher ρ_C implies a lower minimum CAR.

Table D.2.1: Sensitivity Analysis – OLS

	Dependent variable:	
	Credit risk ρ_C	Market Risk ρ_M
	(1)	(2)
ν_{w_1}	-25.123^{***}	-0.125^{***}
	(3.668)	(0.019)
ν_{w_2}		-0.012^{***}
		(0.002)
γ_C		-1.106^{***}
		(0.145)
γ_C^2	-338.588^{***}	2.762^{***}
	(25.154)	(0.843)
ξ_{NBFI}	-42.693^{***}	-0.128^{**}
	(10.553)	(0.055)
ξ_{Funds_B}	37.696^{***}	
	(11.738)	
r_{B_G}	-32.911^{***}	0.085^{***}
	(4.532)	(0.024)
σ_{CH}	-103.567^{***}	0.132^{***}
	(9.453)	(0.049)
σ_{IN}	-11.091^{***}	0.113^{***}
	(1.451)	(0.008)
σ_{NBFI}	-11.441^{***}	0.134^{***}

Continued on next page

	Dependent variable:	
	Credit risk ρ_C	Market Risk ρ_M
	(1)	(2)
	(1.451)	(0.008)
σ_{NPL}	-43.093^{***}	
	(9.431)	
$\bar{\mu}$	-823.896^{***}	1.002^{***}
	(163.133)	(0.022)
$\overline{lev}$	-17.887^{***}	-0.157^{***}
	(5.862)	(0.030)
φ_1	103.696^{***}	-0.003^{***}
	(21.375)	(0.001)
φ_2	-24.677^{***}	0.013^{***}
	(2.919)	(0.0004)
ϖ_1		-0.009^{***}
		(0.001)
λ_λ	-190.164^{***}	-1.057^{***}
	(44.281)	(0.230)
$\lambda_{K_{LC},0}$	-5.449^{***}	-0.082^{***}
	(0.876)	(0.005)
$\lambda_{o,0}$	-3.270^{***}	-0.011^{*}
	(1.172)	(0.006)
ν	-36.287^{***}	-0.636^{***}
	(11.772)	(0.061)
τ_{Tob}	3.102^{***}	0.017^{***}
	(0.472)	(0.002)
ω_p	-1.362^{***}	-0.007^{***}
	(0.317)	(0.002)
$\nu^2_{w_1}$	19.641^{***}	0.085^{***}
	(2.708)	(0.014)
ξ^2_{NBFI}	25.598^{***}	0.088^{***}
	(5.825)	(0.030)
ν^2_u	-168.770^{***}	-0.928^{***}

Continued on next page

	Dependent variable:	
	Credit risk ρ_C	Market Risk ρ_M
	(1)	(2)
	(28.317)	(0.147)
$\xi^2_{Funds_B}$	-250.901^{***}	-0.338^{***}
	(58.681)	(0.024)
r^2_D	$30{,}823.490^{***}$	-89.023^{***}
	(1,829.100)	(9.491)
σ^2_{CH}	$1{,}072.470^{***}$	3.427^{***}
	(149.370)	(0.775)
σ^2_{NPL}	282.390^{*}	2.090^{***}
	(148.643)	(0.119)
$\bar{\mu}^2$	$5{,}044.750^{***}$	
	(1,254.243)	
$\bar{lev}^2$	55.439^{***}	0.334^{***}
	(14.596)	(0.076)
φ^2_1	-6.933^{***}	
	(1.320)	
φ^2_2	2.055^{***}	
	(0.187)	
ϖ^2_2	-0.364^{***}	
	(0.050)	
ϖ^2_1	0.077^{***}	0.001^{***}
	(0.012)	(0.0001)
λ^2_λ	$1{,}640.859^{***}$	8.821^{***}
	(368.492)	(1.913)
$\lambda^2_{K_{LC},0}$	0.680^{***}	0.011^{***}
	(0.146)	(0.001)
$\lambda^2_{o,0}$	1.478^{**}	0.005^{*}
	(0.583)	(0.003)
ν^2	253.227^{***}	2.296^{***}
	(58.680)	(0.304)
τ^2_{Tob}	-2.119^{***}	-0.013^{***}

Continued on next page

	Dependent variable:	
	Credit risk ρ_C	Market Risk ρ_M
	(1)	(2)
	(0.372)	(0.002)
MP 2	-30.439^{***}	-0.096^{***}
	(0.169)	(0.001)
MP 3	-32.395^{***}	-0.095^{***}
	(0.169)	(0.001)
MP 4	-39.456^{***}	-0.135^{***}
	(0.169)	(0.001)
MP 5	-34.842^{***}	-0.108^{***}
	(0.169)	(0.001)
MP 6	-34.156^{***}	-0.113^{***}
	(0.169)	(0.001)
MP 7	-32.329^{***}	-0.101^{***}
	(0.169)	(0.001)
MP 8	-36.119^{***}	-0.077^{***}
	(0.169)	(0.001)
MP 9	-25.379^{***}	-0.071^{***}
	(0.169)	(0.001)
MP 10	-39.828^{***}	-0.122^{***}
	(0.169)	(0.001)
MP 11	-37.890^{***}	-0.055^{***}
	(0.169)	(0.001)
MP 12	-39.704^{***}	-0.136^{***}
	(0.169)	(0.001)
MP 13	-39.052^{***}	-0.120^{***}
	(0.169)	(0.001)
MP 14	-38.619^{***}	-0.100^{***}
	(0.169)	(0.001)
MP 15	-36.903^{***}	-0.122^{***}
	(0.169)	(0.001)
MP 16	-32.066^{***}	-0.103^{***}

Continued on next page

	Dependent variable:	
	Credit risk ρ_C	Market Risk ρ_M
	(1)	(2)
	(0.169)	(0.001)
MP 17	−38.099***	−0.123***
	(0.169)	(0.001)
MP 18	−36.745***	−0.107***
	(0.170)	(0.001)
MP 19	−29.052***	−0.056***
	(0.171)	(0.001)
MP 20	−39.976***	−0.140***
	(0.170)	(0.001)
MP 21	−39.970***	−0.140***
	(0.170)	(0.001)
MP 22	−39.966***	−0.097***
	(0.170)	(0.001)
MP 23	−39.883***	−0.126***
	(0.170)	(0.001)
MP 24	−39.983***	−0.145***
	(0.170)	(0.001)
MP 25	−40.091***	−0.148***
	(0.170)	(0.001)
MP 26	−39.856***	−0.141***
	(0.170)	(0.001)
MP 27	−23.564***	−0.027***
	(0.170)	(0.001)
MP 28	−39.041***	−0.127***
	(0.170)	(0.001)
MP 29	−35.755***	−0.092***
	(0.171)	(0.001)
MP 30	−36.776***	−0.038***
	(0.170)	(0.001)
MP 31	−39.725***	−0.116***

Continued on next page

	Dependent variable:	
	Credit risk ρ_C	Market Risk ρ_M
	(1)	(2)
	(0.170)	(0.001)
MP 32	-39.993^{***}	-0.137^{***}
	(0.170)	(0.001)
MP 33	-39.812^{***}	-0.131^{***}
	(0.170)	(0.001)
MP 34	-39.772^{***}	-0.108^{***}
	(0.170)	(0.001)
MP 35	4.352^{***}	0.070^{***}
	(0.284)	(0.001)
MP 36	-21.888^{***}	-0.030^{***}
	(0.170)	(0.001)
MP 37	-9.383^{***}	0.061^{***}
	(0.170)	(0.001)
MP 38	-39.203^{***}	-0.102^{***}
	(0.170)	(0.001)
MP 39	-34.629^{***}	-0.074^{***}
	(0.170)	(0.001)
MP 40	-35.719^{***}	-0.096^{***}
	(0.170)	(0.001)
MP 41	-36.998^{***}	-0.100^{***}
	(0.170)	(0.001)
MP 42	-15.439^{***}	0.018^{***}
	(0.218)	(0.001)
MP 43	-39.772^{***}	-0.142^{***}
	(0.170)	(0.001)
MP 44	-39.606^{***}	-0.135^{***}
	(0.170)	(0.001)
MP 45	-37.434^{***}	-0.121^{***}
	(0.169)	(0.001)
MP 46	-39.838^{***}	-0.144^{***}

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	Dependent variable:	
	Credit risk ρ_C	Market Risk ρ_M
	(1)	(2)
	(0.170)	(0.001)
MP 47	−39.777***	−0.139***
	(0.170)	(0.001)
MP 48	−39.574***	−0.081***
	(0.170)	(0.001)
MP 49	−39.615***	−0.133***
	(0.170)	(0.001)
MP 50	−39.796***	−0.127***
	(0.170)	(0.001)
SSP 2	−0.226***	−0.001**
	(0.053)	(0.0003)
SSP 3	0.181*	0.002***
	(0.103)	(0.001)
SSP 4	0.215***	0.002***
	(0.064)	(0.0004)
SSP 5	−1.380***	−0.002***
	(0.142)	(0.001)
Constant	−194.737**	0.455***
	(84.707)	(0.029)
Observations	120,350	120,350
R^2	0.694	0.719
Adjusted R^2	0.694	0.719
Residual Std. Error	5.432 (df = 120259)	0.028 (df = 120262)
F Statistic	3,026.870*** (df = 90; 120259)	3,536.040*** (df = 87; 120262)
Note:		*p<0.1; **p<0.05; ***p<0.01
		For SSPs, the reference value is SSP1. For Scenarios, the reference value is Scenario indexed 1.

As can be seen, results are globally aligned with those found in Chapter 2, with nonetheless lower R^2 metrics due to the increased variance across our results. Most parameter values have similar signs and levels of significance, which comforts us in the stability of our model even across many scenarios. However, some differences emerge due to the larger sample on which the OLS is run and the slight change in specification. We focus here on the most meaningful ones. In particular, some effects become linear, like inflation ($\nu_{w,1}$), while retaining the same overall negative sign. Some other variables gain significance, like the NBFI payout ratio ξ_{NBFI}, which exhibits a positive linear effect. It implies that a higher payout ratio may increase the resilience of the system through growth effects but that too high payouts create fragility for the agents. Finally, φ_2 exhibits a non-linear positive effect, which contrasts with the results in Chapter 2. This difference likely emerges due to a larger sample size and a laxer tolerance in the selection of our sensitivity calibration, which may allow us to explore a wider breadth of parameter sets with high φ_2 than in Chapter 2. Similarly, interest rate variables exhibit non-linear positive effects on both indicators. For market risks, the effect is fully positive, highlighting the destabilising effect of interest rate hikes on NBFIs – which we also found in Chapter 2. For credit risk, the linear effect is negative, suggesting that, while incremental interest rate increases may temper credit risks, too high interest rate hikes may endanger the viability of borrowers in a classical Minskian way (Nikolaidi 2017). However, despite these differences, the general picture remains the same as in Chapter 2, increasing the confidence in our tool.

We follow, as in Chapter 2, with an ANOVA decomposition. We only display the outcomes of the 20 most important parameters for brevity. Figure D.2.2 displays our results.

Overall, the variables of interest are the same as in Chapter 2, with slight variations due to the higher number of scenarios we consider and changes in the outcome of interest. We find again the importance of $\lambda_{KLC,0}$ for market risk and the crucial role of interest rate variables in explaining the variance.

Following the results in Table D.2.1, some variables of Table D.2.2 in Chapter 2 are missing from the Top 20 influential variables. Notably, some squared effects become

Table D.2.2: ANOVA Analysis

Credit Risk (ρ_C)			Market Risk (ρ_M)		
Variable	Explained Variance (%)	Significance	Variable	Explained Variance (%)	Significance
Scenarios	64.595	***	Scenarios	66.3797	***
φ_2	2.3424	***	ν_{w_1}	1.5231	***
ν_{w_1}	0.8417	***	$\lambda_{K_{LC},0}$	1.4929	***
$\bar{\mu}$	0.5477	***	σ_{CH}	0.4392	***
$\lambda_{K_{LC},0}$	0.2827	***	$\bar{\mu}$	0.4207	***
σ_{CH}	0.18	***	ν	0.3969	***
σ_{NPL}	0.095	***	γ_C	0.3519	***
r_D^2	0.0692	***	φ_2	0.174	***
ξ_{Funds_B}	0.0448	***	ξ_{NBFI}	0.0821	***
σ_{IN}	0.0393	***	γ_C^2	0.0815	***
SSPs	0.0374	***	φ_1	0.0778	***
σ_{NBFI}	0.0352	***	σ_{NPL}^2	0.0726	***
φ_2^2	0.0328	***	σ_{NBFI}	0.0672	***
ν	0.0306	***	ϖ_2^2	0.0561	***
$l\bar{e}v$	0.0286	***	$\lambda_{K_{LC},0}^2$	0.0548	***
φ_1	0.0284	***	$\xi_{Funds_B}^2$	0.0438	***
r_{BG}	0.0171	***	σ_{IN}	0.0331	***
ν_u^2	0.0145	***	$l\bar{e}v$	0.0274	***
τ_{Tob}	0.0133	***	r_D^2	0.0216	***
σ_{CH}^2	0.0127	***	SSPs	0.0207	***
Total	69.2884		Total	71.8171	

Note : Only the twenty parameters explaining most variance are displayed.

linear, suggesting that outcome variability across scenarios with different patterns is less non-linear than with fewer scenarios. Note also that, due to changes in SSP calibrations, we explore a larger range of crucial parameters governing growth γ_C, and inflation, ν_1 and ν_2, which may result in a different ranking from the one shown in Chapter 2.

Overall, however, changes in our macroeconomic worlds and scenarios explain an overwhelming share of the variance, confirming the importance of considering a wide array of scenarios and hypotheses on macroeconomic conditions. However, only looking at these results should not lead to the conclusion that our parameters are unimportant. Instead, it remains to study how much of the variance in the results of a given outcome for a single Scenario-SSP couple.

D.3. Sensitivity analysis for individual SSP-MP pairs

To do so, we again display in Figure D.3.1 the distribution of explained variances across our Scenario-SSP couples by selecting the best fit with an AIC criterion.

Our analysis shows that most of our parameters have a minimal impact on outcomes,

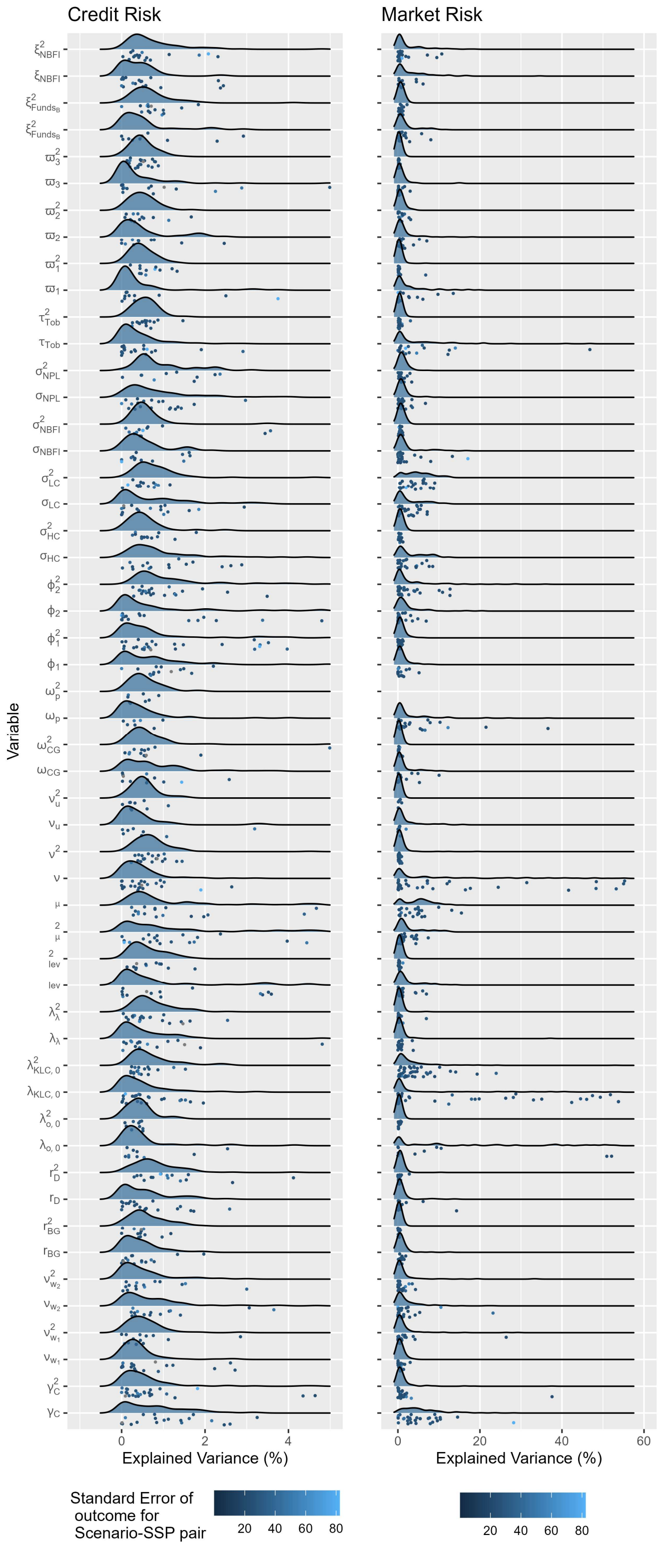

Figure D.3.1: Distribution of explained variance for sensitivity parameters across SSP-Scenario pairs. Bubbles are observations, with colors corresponding to the standard variation of outcome for the corresponding SSP-Scenario pair. Only observations in top-20% of standard error for the outcome are displayed. For instance, a bubble showing on the $xi_{NBFI_s q}$ in Panel (a) gives the share of the variance explained by this parameter in a scenario whose credit risk outcome is within the top-20% of standard errors across SSP-Scenario pairs.

explaining only a share of variance slightly above zero on average. Results are broadly in line with the ANOVA analysis of Table D.2.2, showing a minor dependence on scenarios. For credit risks, explained variance is relatively low across our parameters, ranging between 1 and 2% on average and globally homogeneous. Indeed, outliers, if any, lie relatively close to the distribution mode, as do most values of interest. For market risk, a more significant share of outliers lies far from the mode, with some scenarios driven by one or two parameters. It highlights the higher sensitivity of NBFI default probability to parametrisation already highlighted in Chapter 2. These parameters are the NBFI leverage parameter ν and the cost parameters $\lambda_{KLC,0}$ and $\lambda_{o,0}$, and, to a lesser extent, the passthrough rate and the Tobin coefficient. In contrast to the ANOVA analysis, the passthrough rate seems more critical in some high-variant scenarios, highlighting that some scenario profiles are more sensitive to some parameters. We rely on our parallel coordinate template to link the explained variance to scenario characteristics to disentangle which scenarios exhibit such sensitivity patterns. For brevity, we only perform this analysis for the two parameters with the most significant outliers: ν and $\lambda_{KLC,0}$.

For ν, scenarios are those with low climate-policy efficiency, for mid to mid-high carbon price stringency and steepness. It highlights again the destabilising role of inefficient climate policy. The scenario highly driven by $\lambda_{KLC,0}$ is the low-ambition, slow decarbonisation dynamics and low climate policy pressure. It is fair to assume that, with such an "easy" transition, the cost of low-carbon technology will play a major role in determining outcomes, other scenario hypotheses being relatively innocuous for financial agents. Otherwise, high-stringency scenarios are also driven by $\lambda_{KLC,0}$, which is reasonable, given that less expensive low-carbon technologies may make sharp adjustments less disruptive. Finally, in both cases, we find, again, the higher variability in SSP5 scenarios, highlighting these projections' greater sensitivity to parameter values.

Despite some outliers, the model behaves consistently across scenarios, confirming that a disproportionate source of variance for our results flows from different scenario assumptions. It confirms the need to assess better scenario and model uncertainty in assessing long-run transition risks.

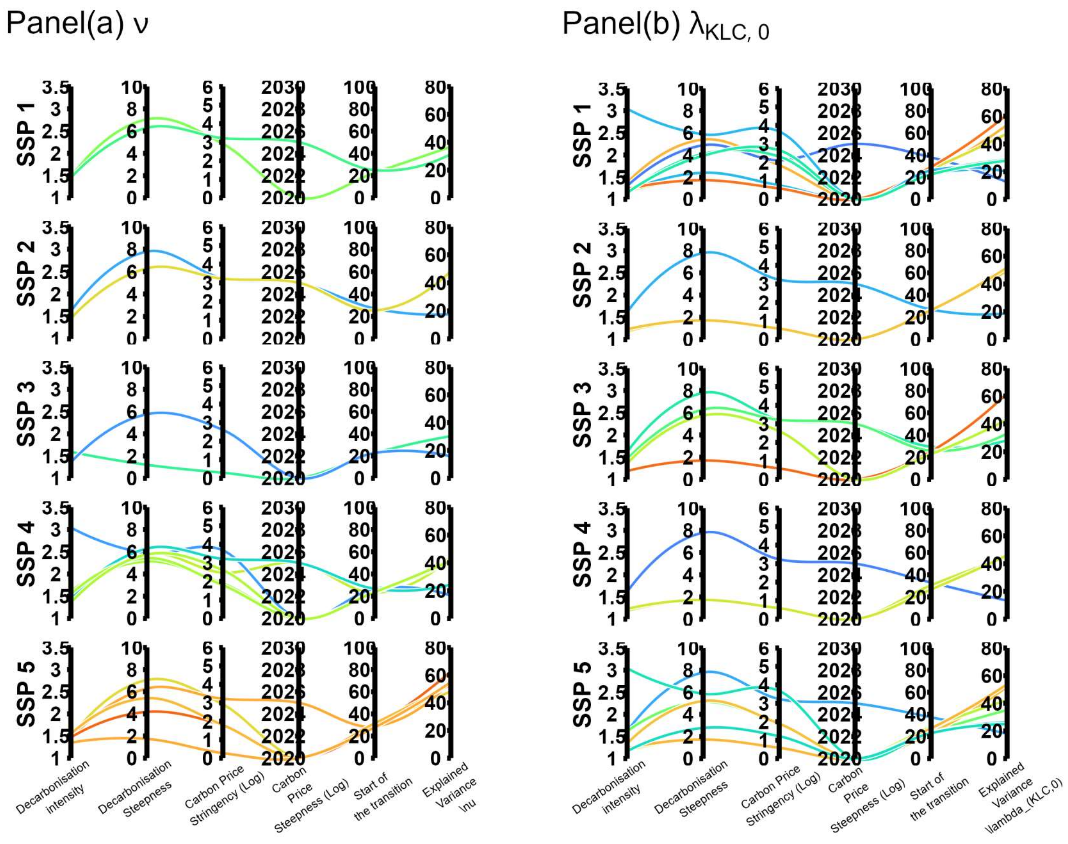

Figure D.3.2: Matching between scenario characteristics and outliers in explaining variance. Color shades correspond to the explained variance. Panel (a) displays results for variable ν (NBFi leverage) and Panel (b) displays those for $\lambda_{KLC,0}$ the starting value of the productivity of low-carbon capital production, which influences the cost of low-carbon technology. Only observations explaining a high share of the variance are displayed, and only scenarios in the top-75% of outcome variance are displayed.