Climate Risk Stress Testing: A Conceptual Review[*]

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March 2023

Abstract

We conceptually review Climate Risk Stress Testing (CRST) approaches to assess the impact of climate-related shocks on financial system stability. We distinguish between climate, economic, and financial modeling steps, and identify six types of climate shocks and four different approaches (macro-financial, micro-financial, non-structural, and disaster risk). Our review identifies several key limitations in current CRST approaches: (i) neglect of certain climate shock types (Green Swan and Minsky-type events); (ii) overreliance on macro models (with low sectoral and spatial granularity); (iii) incomplete modeling (lack of feedback effects); and (iv) limited scope (subset of causal channels and asset classes). We argue that these limitations may lead to significant underestimation of potential system-wide financial losses and offer suggestions for improving CRST approaches.

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The authors are grateful to Jean Boissinot, Dion Bongaerts, Wouter Botzen, Jean-Stéphane Mésonnier, Romain Svartzman, colleagues at the World Bank and the International Monetary Fund, and participants at the 2021 Stress Testing Research conference of the Federal Reserve for stimulating discussions and useful suggestions. The opinions in this paper are those of the authors and do not necessarily coincide with those of the International Monetary Fund.

1. Introduction

Climate change and the associated policy measures to mitigate Greenhouse Gas (GHG) emissions pose a novel challenge for central banks and financial supervisors and their traditional ways of gauging potential losses from severe adverse events. While financial risk methodologies are typically assuming that the future will be similar to the past, climate change is likely to lead to fundamental and often detrimental changes over time in a broad set of regions and economic sectors (Intergovernmental Panel on Climate Change, 2022). The economic costs related to climatic change are potentially very high, for example due to the increasing frequency and severity of natural disasters and sea-level rise in many regions of the world (e.g., Tol, 2002). Moreover, reducing GHG emissions to limit climate change is expected to come at an economic cost in many economic sectors, at least in the short run (Acemoglu et al., 2012; Nordhaus, 1992). This means that, one way or another, it is likely that a broad range of economic and financial assets will face changes in their value.

From the perspective of regulators concerned with the health of the financial system, a key question is what the potential impacts of climate change and its mitigation are on the profitability, solvency, and liquidity of banks (Campiglio et al., 2018). Efforts in recent years by central banks and financial supervisors have focused on understanding and gauging climate-related financial risks, including "transition risks", which capture structural changes in the economy due to GHG emission reduction, and "physical risks", which capture the effects of a changing climate (Batten et al., 2016; Nieto, 2019). Of specific interest are transition and physical risk scenarios that could cause large economic and financial losses, impeding financial stability.

To assess risk scenarios that could cause large losses, financial sector stress testing is an often-used technique that measures the vulnerability of a portfolio, a financial institution, or an entire financial system under different hypothetical events or scenarios (Ong and Jobst, 2020). Stress tests are designed to estimate what would happen to financial sector variables under adverse (i.e., severe but plausible) circumstances, that have not materialized yet. Stress testing per definition looks at extreme scenarios in the spectrum of all possible scenarios. Risks investigated are hence in the tail end of the scenario probability distribution (Slijkerman et al., 2013; Bolton et al., 2020). Traditional macro-financial stress testing approaches based on estimated GDP impacts may, however, underestimate losses in adverse scenarios, amongst others due to limitations in neoclassical economic modeling (Keen, 2021) and the potential for unknown and highly non-linear “tipping points” occurring (Lenton, 2008; Armstrong McKay et al., 2022). It is hence important to develop new climate risk stress testing approaches.

Stress tests usually involve a form of modeling, i.e., a function that maps input variables to the financial system variables of interest. Typically, a financial system stress test model consists of at least four elements (Borio et al., 2014). This includes one or more (climate) shock scenarios, a model to translate (climate) shock variables to (macro)economic variables, a model to translate (macro)economic variables to financial sector variables, and a stress test model to apply shocked financial sector variables to financial institutions’ balance sheets as well as profit and loss accounts (see Figure 1). Models to translate (macro)economic variables to financial sector variables are sometimes also referred to as “satellite models” (Oura and Schumacher, 2012). Furthermore, financial system stress tests may include one or several feedback loops between key variables, such as amplification within the banking sector and “credit crunches” whereby the supply of credit to the economy declines sharply (e.g., Acemoglu et al., 2015; Silva et al., 2018). These feedback loops may cause additional financial losses.

A specific strand of stress testing research has emerged that investigates the effects of adverse climate and climate policy shocks on financial portfolios and the financial system as a whole (e.g., Battiston et al., 2017; Allen et al., 2020; Jung et al, 2021; Reinders et al., 2023). This paper contributes to this emerging literature in three ways. First, we survey the stress testing methods that have been developed to date. Second, we conceptually classify scenarios and approaches to climate risk stress testing. And third, we discuss the models that constitute climate risk stress tests.

Our results are relevant for both academics and practitioners that design climate risk stress tests. Stress test outcomes should feed into policymaking and risk management to take action to avoid or reduce the impact of adverse scenarios. This is in particular the case for central banks and financial sector prudential supervisors, whose main aim is to ensure the stability of the financial system and to make sure that financial commitments (including to retail depositors and policyholders) can be met even in highly adverse circumstances. Financial institutions should also feed stress test outcomes into their risk management policies. Actions by public authorities and private institutions to reduce the impact of adverse scenarios can speed up the transition (e.g. financial institutions rapidly reducing exposures to carbon-intensive industries).

This paper is organized as follows. In Section 2, we first discuss the stress testing of climate-related financial risks and the features that make it different from traditional stress testing. Section 3 then proceeds by reviewing the “building block” models that are employed to understand the climate-financial relationship. In Section 4, we identify and discuss four common typologies that have emerged (traditional macro-financial, micro-financial, non-structural, and disaster risk). Section 5 classifies and reviews the main top-down exercises that have been carried out so far while the last section concludes and provides avenues for further research.

2. Climate Risk Stress Testing (CRST)

We define Climate Risk Stress Testing (CRST) as a technique that measures the vulnerability of a portfolio, a financial institution, or an entire financial system to adverse climate-related hazards and scenarios.[1] A typical example of a climate related hazard would be an isolated extreme weather event, such as a typhoon or flood occurring, while climate scenarios usually focus on a wider set of variables changing over time, such as changing weather patterns, changing economic structures or changing climate policies. In the remainder of this paper, we use the term "climate shocks" to refer to both acute climate hazards and chronic climate change scenarios.

Climate-related risks have several unique characteristics that set them apart from traditional financial sector risks. First, climate change is characterized by deep uncertainties and complex non-linear effects that materialize over an extended period of time (Weitzman, 2009; Monasterolo, 2020). Second, most climate change variables are thought to change gradually over a relatively long time horizon, which implies that the most severe effects occur decades or even centuries from now. Third, the level of climate change mitigation is the outcome of a complex socio-economic process where potential financial losses by investors and lenders may, in turn, affect the level of ambition of climate policies, such as putting a price on carbon. Fourth, climate change does not only affect the economy but also vice versa since virtually all economic activity is associated with at least some GHG emissions (Battiston et al., 2017).

To assess climate-related financial risks, CRST needs to be able to translate initial parameters (i.e., a climate shock) into variables that are relevant to assess the impact on financial system (e.g., solvency and liquidity ratios). Since climate-change scenarios usually have no precedent in history there is a need for more fundamental (structural) models to

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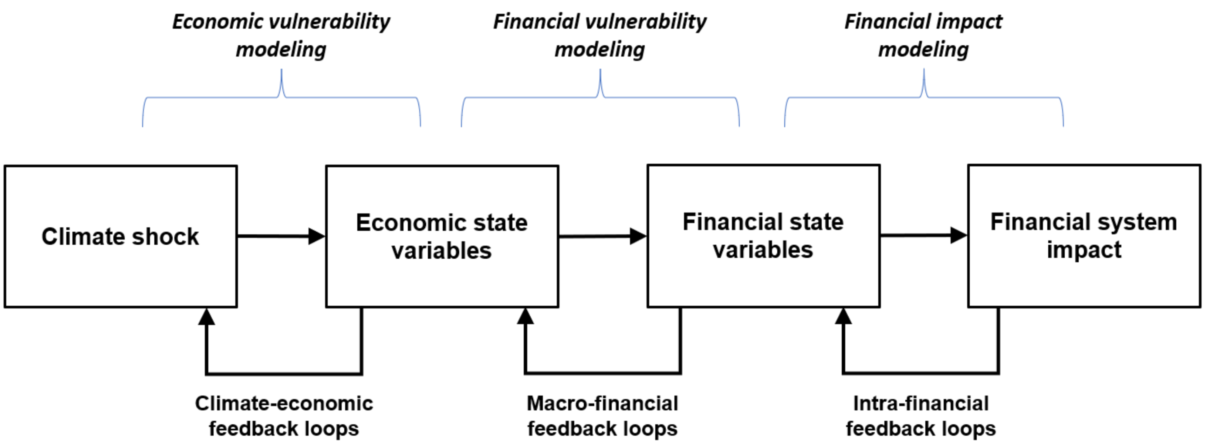
[1] Hazards usually referring to a single risk factor while scenarios usually involve multiple risk factors evolving over time. It is common practice in financial sector stress testing to measure financial impact as the differential in the outcome variable (e.g., capital adequacy) compared to the situation with either no hazard or a baseline scenario occurring. Hence, besides the shock scenario a baseline scenario is needed.

estimate the impact of climate scenarios on financial institutions. This in contrast to traditional stress testing exercises in which the shock parameters are mostly calibrated on historical events, such as GDP impacts in past financial crises (Allen et al., 2020). Since both transition and physical risks have asymmetrical sectoral and spatial impacts, this has increased the need to use approaches to risk assessment that are more granular (e.g., approaches at a sector, firm and asset level) than the traditional macro-level approaches. Figure 1 provides a conceptual model for CRST depicting the main modeling steps, generalizing the modeling steps presented in Borio et al. (2014) by labelling the intermediary steps "economic state variables" and "financial state variables".[2] There are also relevant feedback effects between the different dependent, independent, and moderating variables. These include systemic feedback effects within the financial sector, feedback effects from the financial sector to the economy, and feedback effects from the economy to climate variables. A combination of these feedback loops could cause feedback loops all the way from the financial system back to climate shocks (e.g., when a financial crisis leads to an economic downturn that reduces mitigation efforts).

Figure 1 – Conceptual model from climate shocks to financial system impact



Besides the modeling through economic and financial variables, which is arguably the most important overall channel, there are conceivably more direct channels that are relevant within the CRST context. This includes climate-related shocks that have a direct effect on financial state variables or financial institutions (i.e., not through economic state variables). First, this could occur due to pricing effects based on green consumer preferences, also referred to as a "greenium" (Alessi et al., 2021). Second, there may be direct effects of climate-related

[2] We generalize these steps since for CRST we find that economic modeling at the micro (e.g., firm) level is becoming more common – contrasting the traditional approach through macroeconomic variables.

shocks on the pricing and valuation of weather and disaster linked financial instruments, such as catastrophe bonds (Lakdawalla and Zanjani, 2012).[3] Third, direct effects on financial institution solvency could occur when prudential regulation would incorporate climate-related elements in determining capital requirements, such as a green supportive factor or a brown penalizing factor (Boot et al., 2022).

2.1 Climate shocks

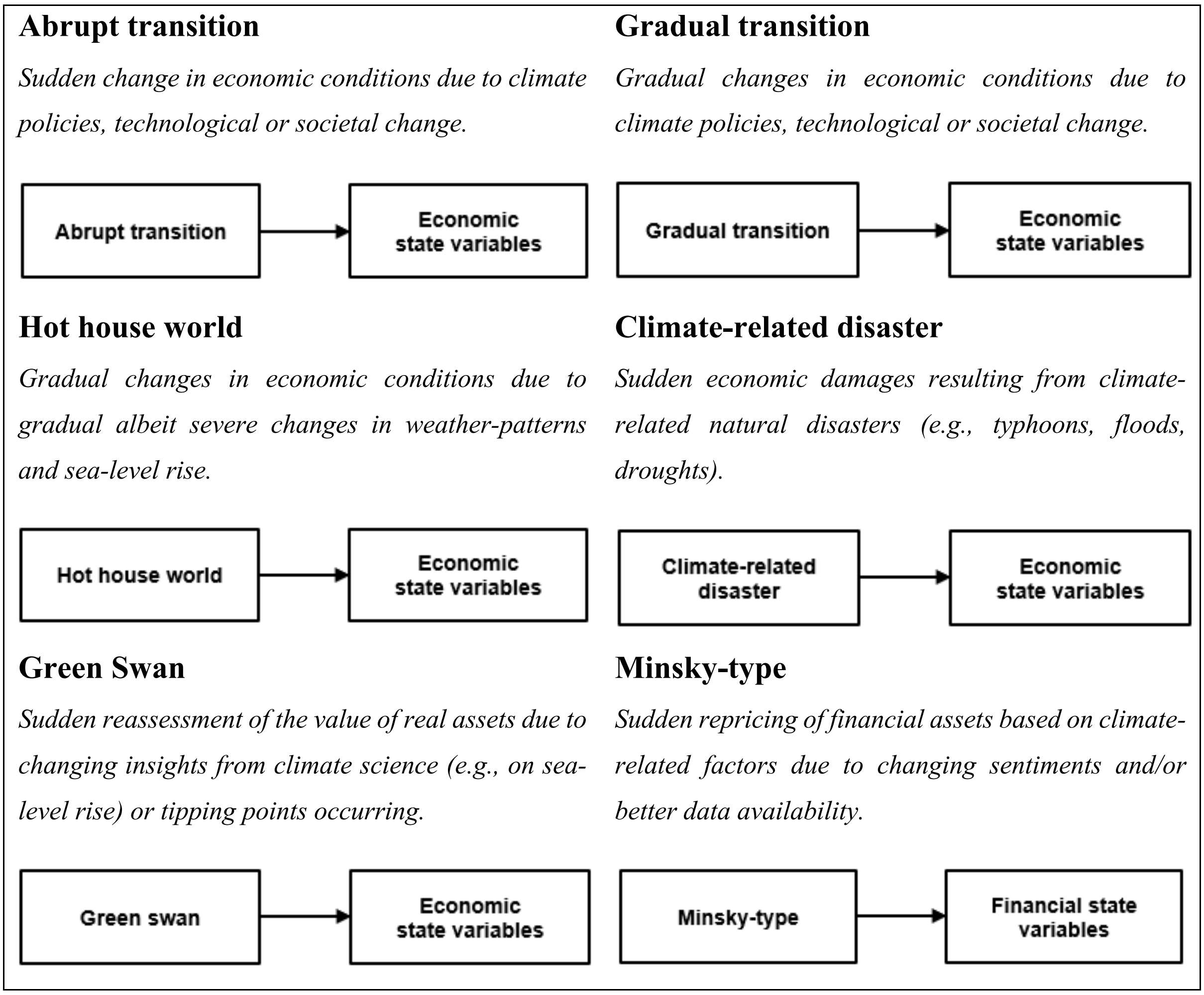
Climate change can lead to several types of adverse shocks to the financial system. We identify six types of shocks, summarized in Figure 2. The first three shocks (abrupt transition, gradual transition, and "hot house world" are well established in the climate stress testing literature and distinguish themselves along two dimensions: either an orderly or disorderly transition and either low or high global warming – the high warming scenario referred to as a "hot house world" (Steffen et al., 2018; Network for Greening the Financial System, 2022). We omit the scenario with an orderly transition *and* low global warming as this scenario does not fall in the adverse category that is suitable for climate stress testing. A fourth type of shock (climate-related disaster) is based on an emerging literature that investigates scenarios related to the occurrence of one or more climate-related natural disasters on financial institutions (e.g., Klomp, 2014; Schüwer, Lambert and Noth, 2019; Hallegatte et al., 2022). These shocks are relevant in a climate change context, since climate change is expected to affect the frequency and intensity of natural disasters (Intergovernmental Panel on Climate Change, 2022), including tropical cyclones (e.g., Knutson et al., 2010) and floods (e.g., Hirabayashi et al., 2013; Arnell and Gosling, 2016). This is in particular the case for the most extreme disasters, whose frequency is expected to increase substantially due to climate change (Coronese et al., 2019).

Furthermore, we argue that financial sector losses can occur when financial sector agents suddenly change their perception of current and future risks, which would be rapidly reflected in today's market prices of financial instruments. In the climate context, this could chiefly be for two reasons. First, a shock could emanate directly from our changing perception of the state of the global climate system. This could include the unexpected occurrence of climate tipping points (Lenton, 2008; Bolton et al., 2020; Armstrong McKay et al., 2022) or changing insights from climate science – for example when research would find that sea-level

[3] As far as we are aware, direct effects have to date not been incorporated in CRST exercises. The effect of pro-environmental preferences on bond prices is found to be limited to date (e.g., Zerbib, 2019).

rise occurs more quickly than previously thought. Bolton et al. (2020) label these tipping points and changing insights as a “Green Swan” event. Second, a shock could emanate from the financial sector if it fails to continuously incorporate the latest climate science and financial sector agents suddenly do so at some point in time – for example due to increased awareness, a large natural disaster event, or strongly improved climate risk data. We label the latter as a “Minsky-type” shock (Minsky, 1992). The main difference between the two types of shocks is whether it is economic or financial state variables that change suddenly. A Green Swan shock represents a sudden change in understanding of economic fundamentals, while a Minsky-type shock emanates from a disconnect between economic fundamentals and financial asset values that is suddenly corrected. While economic fundamentals can change gradually under a Minsky-type scenario, financial shocks could be sudden when investor sentiment changes. Such scenarios could especially occur in environments where there is a lack of adequate data, understanding, and transparency to price and assess financial risks.

Figure 2 – Classification of climate shocks



3. CRST building blocks

In this section, we review the main underlying models used in CRST exercises, distinguishing between economic vulnerability, financial vulnerability and stress test modeling steps in line with the conceptual model provided in Figure 1. We specifically focus on the level of analysis and main moderating variables that are relevant as part of the modeling. Table 1 provides an overview of the models, which modeling step they are mainly used for (i.e., economic vulnerability, financial vulnerability, or financial system impact), and their level of analysis, and the CRST exercises that they are applied in. We discuss each model in turn in the next sections.

Table 1 – Models used in CRST

Model	*Modeling step*	*Level of analysis*	*Applied in*
1. Computable General Equilibrium (CGE)	Economic vulnerability	Macro or sector	• World Bank Group (2021)
2. Macro-structural models	Economic vulnerability	Macro	• Vermeulen et al. (2018) • Allen et al. (2020)
3. Integrated Assessment Models (IAMs)	Economic vulnerability	Macro	• Allen et al. (2020) • European Central Bank (2022)
4. Firm valuation models	Economic vulnerability	Firm	• Reinders et al. (2023)
5. Disaster risk models	Economic vulnerability	Location / asset	• Hallegatte et al. (2022)
6. Macro-financial (satellite) risk models	Financial vulnerability	Asset class	• Vermeulen et al. (2018) • Allen et al. (2020) • European Central Bank (2022) • Grippa and Mann (2020)
7. Structural credit risk models	Financial vulnerability	Firm / asset	• Reinders et al. (2023)
8. Non-structural empirical models	Financial vulnerability	Firm / asset	• Jung et al. (2021)
9. Financial impact models	Financial system impact	Bank	• Battiston et al. (2017) • Vermeulen et al. (2018) • World Bank Group (2021) • Hallegatte et al. (2022)

3.1 Computable General Equilibrium (CGE) models

Computable General Equilibrium (CGE) models are economy-wide models that focus on the long-term effects of policy changes. The focus of these models is on the longer-term effects of large-scale reforms of the economy, such as subsidy reforms and carbon taxation (Burns et al., 2009). CGE models typically integrate Input-Output (IO) tables or Social Accounting Matrices

(SAMs) as a result of which CGE models tend to have a high sectoral detail compared with macrostructural models.[4] CGE models provide a richer analysis than using merely IO tables or SAMs, as they account for price and behavioral changes endogenously while applying macroeconomic constraints such as the supply of labor (Anvari et al., 2022). This makes CGE models especially suitable to analyze the economic effects of carbon taxation across economic sectors in an economy.

Firm and consumer behavior is usually assumed to be fully flexible, with each reacting to changes in incentives in a way that is consistent with economic theory. Due to this assumption, outcomes of CGE models tend to be most valid for longer time horizons. For shorter time horizons, non-modelled frictions in the economy (e.g., in the labor market) may cause CGE models to underestimate economic damages from a policy shock (such as a change in carbon tax regime). This could also be the case due to supply-side constraints, such as having enough suitable areas to deploy wind and solar power. Moreover, assumptions are needed on structural changes in the economy due to product and process innovation, including those driven by technological progress. This is especially relevant when modeling longer run transition scenarios, since economic costs and gains related to decarbonization depend strongly on the availability and cost of low-carbon alternatives, such as renewable energy sources.

3.2 Macrostructural models

Macrostructural models use econometrically estimated parameters to establish relations between key economic variables, such as relative prices, changes in employment, unemployment, and inflation. The underlying structure of macrostructural models is based on economic theory and usually focuses on short-term disequilibrium behavior in the economy following an initial shock. Usually, these models have a less rigid theoretical foundation than DSGE or CGE models (Blanchard, 2018). In comparison to CGE models, macrostructural models are better able to reflect frictions such as delayed responses by households and industries to changing relative prices (Burns et al., 2009). This addresses non-modelled frictions and associated potential underestimations of economic impact by CGE models and makes macrostructural models especially suited to investigate shock scenarios.

A key example of a macrostructural model is the National Institute Global Econometric Model (NiGEM) model, which has been used by the Network for Greening the Financial

[4] Input-output (IO) models focus on interactions between different sectors in the economy, thereby providing insight in the flow of goods as intermediate inputs for final consumption. They provide a static picture of the economy by using fixed-coefficients for the cost structure of firms (e.g., Leontief, 1951, Ghosh, 1958).

System (NGFS) to determine the evolution of economic variables that are not present within IAM frameworks. NiGEM consists of linked individual country models. Country models are economy-wide systems of dynamic equations. It is New Keynesian in structure in that it assumes agents with rational expectations and there are nominal rigidities that slow adjustment process to external shocks (Hantzsche et al., 2018). A main drawback of macrostructural models is that they usually do not have the same level of sectoral detail as CGE models, making them less suitable when considering micro or sector level financial exposure data. Another limitation of these models is that they are reduced-form models and not structural. They are based on historical relations which may become invalid in the presence of large shocks such as structural changes in climate policies (Lucas, 1976; Anvari et al. 2022).

3.3 Integrated assessment models

Integrated Assessment Models (IAMs) encompass approaches that integrate knowledge from two or more domains into a single framework. IAMs have been extensively used to model the interplay between GHG emissions, changes in climate and sea level, and economic variables (e.g., Nordhaus, 1992; Tol, 2002). Many are developed to analyze the expected costs and benefits of climate policies and determine optimal transition paths to reduce GHG emissions (Weyant, 2020). From a climate risk stress testing perspective, IAMs provide a link between climate and economic outcomes, including feedback loops from economic outcomes to climate variables over time (chiefly through GHG emissions). This allows for the construction of decarbonization trajectories as well as expected damages from climate change over time.

IAMs differ in their complexity and interconnections that they consider. This includes the degree of technological detail, the degree of sectoral detail, the availability of mitigation technologies and options, and the method by which they reach a solution for each time period (Gambhir et al., 2019).[5] One of their important uses has been within the context of the IPCC assessment reports, to quantify the effect of climate mitigation in different shared socio-economic pathways (SSPs) (Intergovernmental Panel on Climate Change, 2022). The focus of IAMs is on long term horizons, up until 2050 and beyond (e.g., Rogelj, 2018). This makes them less suitable to assess more adverse scenarios from a stress testing point of view, such as the sudden introduction of climate policies or the occurrence of a natural disaster. IAMs have been criticized for using unrealistic and unchallenged assumptions which could lead to an

[5] Six widely used models in global mitigation scenario analysis are IMAE, MESSAGE-GLOBIOM, AIM/CGE, GCAM, REMIND-MAgPIE, and WITCH-GLOBIOM. Three of these models have also been used to develop the scenarios for the NGFS (Network for Greening the Financial System, 2022).

underestimation of the economic costs due to climate change. These critiques concern the use of financial discount rates instead of typically lower social discount rates (e.g., Dasgupta, 2008; Stern, 2008) and a systemic and gross underestimation of damages from unmanaged climate change (Stern, 2018), including classifying a large fraction (up to 90 percent) of GDP as unaffected by climate change (Keen, 2021).

3.4 Firm valuation models

Discounted Cash Flow (DCF) models are used in finance to value firms and other types of assets (e.g., real-estate) by estimating the cash flows that they produce over their lifetime (e.g., Berk and DeMarzo, 2020). Cash flows are then adjusted using a time dependent discount factor to account for investor preferences (such as risk aversion and the time value of money). In this setting, the impact of carbon pricing policies on firm valuation can be investigated by including a cost of carbon as a negative cash flow. The estimated impact of this negative cash flow on firm valuation can then be linked to a Merton structural credit risk model to estimate market value changes in the firm's equity and debt (Reinders et al., 2023). To estimate the effect of a carbon tax on firm value it is necessary to include parameters on cost pass-through and firm-level emission abatement potential (e.g., Fabra and Reguant, 2013; Smale et al., 2006). This methodology can be used to estimate effects at asset level, hence increasing the precision of the analysis, but is limited to the direct effect of carbon taxation hence potentially leading to an underestimation of total losses in financial portfolios.

3.5 Disaster risk models

Catastrophe (CAT) modeling has been developed since the 1980s, mostly from a practical perspective to manage property insurance risks. According to Mitchell-Wallace et al. (2017), most catastrophe models adopt a modular approach that consists of a hazard module (simulating a set of potential adverse events, such as hurricanes or floods), a vulnerability module (providing damages as a function of the intensity of the hazard), an exposure module (providing exposure data such as location, characteristics and value of objects), and a financial loss module (calculating for example insured losses). This fits to our conceptual model in that catastrophe modeling combines the full chain between climate events and financial loss for insurers.

Typical CAT models do not consider the changes in disaster frequencies in the future due to climate change since property insurance contracts are usually annually renewed. However, for climate stress testing purposes, the hazard module of catastrophe risk models can be recalibrated to represent a future climate condition (Ranger and Niehörster, 2012). The future path of climatic hazards can be estimated using global or regional climate models, for example for hurricanes (Bender et al., 2010) and floods (Winsemius et al., 2013). Furthermore, the standard outputs of CAT models for insurance companies (e.g., estimated damages) can be combined with a macroeconomic model to estimate a broader range of relevant economic state variables such as GDP and unemployment over time (Hallegatte et al., 2022) making them suitable for stress testing financial institutions other than insurers as well.

A main drawback of CAT models is the limited historical data that is available for calibration of the model and making future projections, especially for the tail ends of the distribution. Although it is possible to use Extreme Value Theory (EVT) to estimate the probability and magnitude of disasters outside of the observed historical sample (e.g., Embrechts and Resnick, 1999), deep uncertainty remains in projecting disaster risks into the future (Weitzman, 2009; Ranger and Niehörster, 2012). Furthermore, most financial institutions other than insurance (for whom CAT modeling is traditionally developed) do not have data available on the precise geographical locations of the assets that they finance, which may include firms that have productive assets in different locations.

3.6 Macro-financial (satellite) models

Since macroeconomic models usually do not include measures of financial risks, stress testing involves the estimation of auxiliary or satellite models that link a measure of financial risk to macroeconomic variables. Specifically, satellite models are used to determine credit losses and various components of profit, including funding costs, under various scenarios (Jobst et al., 2013). Those auxiliary or satellite models often take the form of (panel) regression models with commonly employed methods being (i) structural econometric models, (ii) vector autoregressive (VAR) models, and (iii) pure statistical approaches (Foglia, 2009).

An early example of such approach is given by Blanschke et al. (2001) who regress the nonperforming loan (NPL) ratio against a set of macroeconomic variables including the nominal interest rate, the inflation rate, the change in real GDP, and the change in the terms of trade. A recent example of a VAR approach is provided by Gamba et al. (2017) who estimate the proportion of loans that is in a certain credit rating category for different asset classes. They include GDP growth, the interest rate on mortgage and corporate loans, the house price index, and the unemployment rate as independent variables. Since satellite models treat macroeconomic variables as exogenous this implies that any feedback effects from a distressed financial sector to the economy are not taken into account. Another drawback of this approach is that it implicitly assumes that climate-related economic shocks have similar effects as the economic shocks that occurred in the past and were used to perform the regression modeling. It hence has little specificity to climate-related shocks.

3.7 Structural credit risk models

Structural credit risk models have been developed to value financial instruments, including options and debt positions (e.g., Scholes and Black, 1973; Merton, 1974). Structural factors that determine the market value of debt include leverage, the interest rate, and asset value volatility. Merton's key insight is that equity can be viewed as a residual claim on assets after the debt has been repaid (Merton, 1974). This implies that the equity holder has a call option on the value of the firm's assets, where the payoff is the maximum of (since a corporation has limited liability) and the value of firm's assets minus the face value of the debt. Conversely, the debt holder has a risk-free bond and is short a put option of the firm's assets. Overall, Merton's contingent claims approach implies that a negative asset valuation shock will affect the value of both equity and debt in a non-linear manner. This is especially important when considering asymmetric shocks that affect some debt claims to a higher extent than others, which is characteristic for both physical risk, where especially assets in some geographic regions could be affected, and transition risk, where especially assets in certain transition-sensitive industries could be affected (Battiston, 2017).

Structural credit risk models can be used to distribute firm-level asset valuation shocks to the holders of equity and debt and can thereby be used for stress tests with highly granular (e.g., firm level) data. A main drawback of structural credit risk models is that their simplified structural form is not always applicable to the portfolios under investigation and its assumptions (e.g., firm asset value follows a random walk, firms have only one type of plain vanilla debt) do not always hold, resulting in potentially biased estimates of credit risk. Specifically for secured loans, such as most European mortgages, the standard Merton model may overestimate potential losses and adjustments to the model are needed (Reinders et al., 2023).

3.8 Non-structural empirical models

Besides the more traditional satellite models that are mainly used for credit risks there is a broader class of empirical approaches that can inform financial sector stress testing. This usually involves investigating a more "direct" relation between scenario variables and financial sector variables, such as financial asset value or financial institution solvency. For example, Klomp (2014) investigates to effect of natural disasters on the distance-to-default of banks and Scholtens and van der Goot (2014) investigate the effect of carbon prices on stock prices of firms in different industries. There are also studies investigating the effect of natural disasters on sovereign credit ratings, which allows the inclusion of a sovereign bond channel in the stress testing (e.g., Standard & Poor's, 2019).

In general, these approaches allow for the estimation of elasticities between the independent and dependent variables, which both may have several time lags. Empirical models are mostly suitable to assess scenarios that have already occurred in the past and hence historical events are available to estimate a direct relation. This is challenging for adverse transition risk scenarios, where historically carbon price shocks are found to be incremental and relatively benign in their impact on financial asset values (e.g., Scholtens and van der Goot, 2014).

3.9 Financial impact models

As a final step in most stress testing approaches, the estimated changes in financial sector state variables are linked to financial institution specific variables to obtain a measure of overall impact. According to Oura and Schumacher (2012), two main approaches are used: models that build on a detailed analysis of balance sheets of individual institutions (sometimes called "fundamental approaches") and models based on summary default measures for individual assets, institutions, or entire financial systems as embedded in market prices (such as stocks, bonds, and derivatives). The fundamental approach consists mostly of accounting-based translation of the estimated impact on financial sector state variables to metrics such as capital and liquidity ratios (e.g., Cihak, 2007; Schmieder et al., 2011). Depending on the granularity of the balance sheet data, this assessment can be at the sectoral or individual financial institution level. The market-price based approach derives implicit default probabilities using option price models (Gray, 2007). It can amongst others be used to translate estimated impacts on financial sector state variables into expected or unexpected losses at market value at the portfolio, institution, or sector level.

Besides the first-round (direct) impacts of climate scenarios, financial sector dynamics and feedback loops to the real economy may lead to asset price revaluations and shocks to financial institutions that are much larger than the initial shock. Three effects that have been identified in the literature are amplification within financial networks (e.g., Acemoglu et al. 2015; Allen et al., 2012; Battiston and Martinez-Jaramillo, 2018) also referred to as "financial contagion", feedback loops to the economy due to a reduction in available finance (credit crunch; see, for example, Silva et al., 2018), and interactions between financial losses and sovereign credit spreads due to sovereign contingent liabilities in the case of the default of financial institutions (in particular, banks) also referred to as "doom loops" (e.g., Farhi and Tirole, 2018).

4. CRST modeling approaches

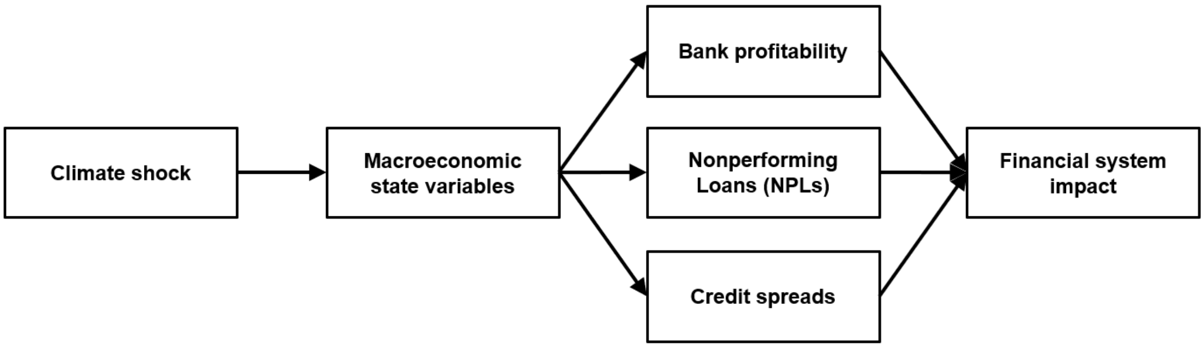
In this section, we identify and discuss four typical climate-financial modeling approaches, based on the currently existing CRST exercises and available economic and financial models. One key observation in the development of CRST is the emergence of more granular modeling approaches next to the traditional macro-financial approaches, leveraging on the sector specific and/or location specific impacts of most climate shocks. Taking a more micro approach at sector, firm, or asset level allows for more precise allocation of risks to financial institutions based on their sectoral and spatial asset exposures, which helps to identify those institutions that are most at risk. This micro approach allows central banks and supervisory authorities to assess microprudential risks next to the more macroprudential (systemic) ones. Furthermore, specific approaches have been developed that are less structural in nature. For example, Battiston et al. (2017) largely set aside the need for economic and financial modeling by assuming a full loss of financial value in selected climate-policy relevant sectors. Finally, specifically for disaster risk shocks, stress test have been developed that build on the disaster risk models traditionally employed in the (re)insurance industry. We describe each modeling approach in turn.

4.1. Macro-financial (traditional) approach

The macro-financial approach builds on a well-established approach to do climate stress testing (e.g., Jobst et al., 2013; Ong and Jobst, 2020) and is characterized by the translation of climate shock variables into macro-economic variables such as GDP, unemployment, and inflation.

Differences in those variables compared to a baseline scenario are then used to estimate (i) accounting based financial risk measures, such as changes in nonperforming loans (NPLs) and/or (ii) market based financial losses, such as changes in expected losses on loan portfolios or market value of tradable securities. This second step is usually mostly non-structural in nature, using regression models to estimate relations between economic and financial variables. The main models used in this approach are macroeconomic models such as CGE models, IAMs, and macro-structural models. Since macroeconomic variables usually cannot be structurally linked to financial outcomes, the financial models used are typically empirical in nature (i.e., macro-financial satellite models). Figure 3 depicts a typical macro-financial approach, with satellite models for bank profitability, NPLs, and credit spreads.[6]

Figure 3 – Typical macro-financial approach



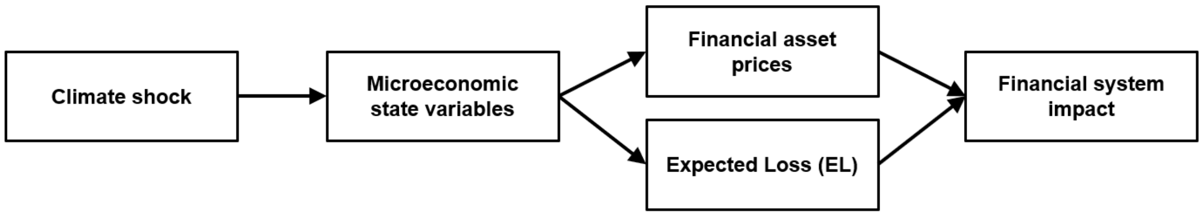
4.2. Micro-financial approach

The micro-financial approach is characterized by the translation of climate shock variables into micro-economic state variables at firm or asset level, such as earnings, enterprise value, and leverage. The main economic models used in this approach are valuation models, often based on discounted cash flow (DCF) analysis. Differences in variables compared to the baseline scenario are then used to estimate (i) accounting based financial risk measures, such as changes in nonperforming loans (NPLs) and/or (ii) market based financial losses, such as changes in expected losses on loan portfolios or market value of tradable securities. This second step can be both structural (e.g., based on option pricing models) or non-structural in nature, using

[6] The depicted satellite models are not exhaustive and other mediating financial variables have been used as well (e.g., interest rates, provisions, and stock prices).

regression models to predict financial risk parameters such as asset level probability of defaults. Figure 4 depicts a typical micro-financial approach.

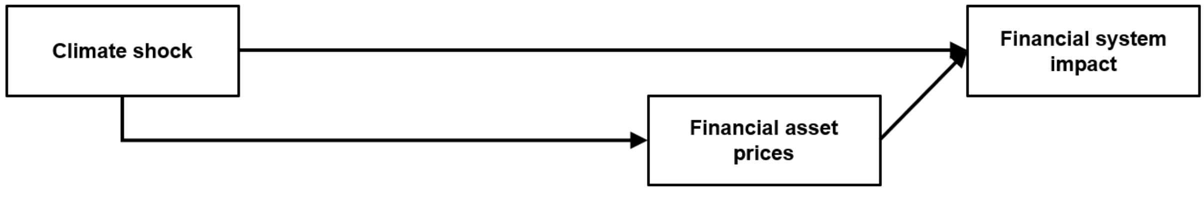
Figure 4 – Typical micro-financial approach



4.3. Non-structural (direct/empirical) approach

This approach is characterized by treating the economic effects of a shock as a black box and directly modeling the relation between the climate shock and the financial outcomes. Usually, these approaches are empirical in nature (e.g., Jung et al., 2021, Klomp, 2014). However some studies investigate worst-case scenarios where it is assumed that assets in certain sectors lose their value completely (e.g., Battiston, 2017). Since very few mediating and moderating variables are used, this approach is mostly suitable to stress test events that have already occurred in the past, such as large natural disasters. In the non-structural approach, it is not clear which economic and/or financial channels are affected under the climate scenario. Some studies have attempted to estimate the effect of carbon taxation on equity prices, however the investigated shock size has been limited so far (e.g., Scholtens and van der Goot, 2014). Figure 5 depicts a typical non-structural approach, with dependent variables being either financial asset prices or financial institution viability indicators (such as the capital adequacy ratio).

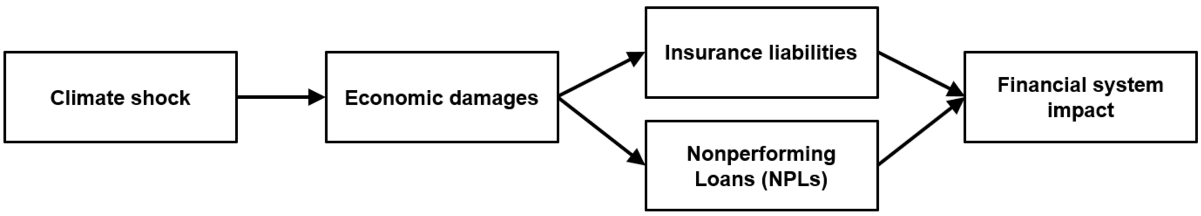
Figure 5 – Typical non-structural approach



4.4. Disaster risk approach

The disaster risk approach is characterized by the linking of disaster risk models used in the (re)insurance industry to financial sector outcomes, through variables such as economic damage and total factor productivity (TFP). These variables can in turn be linked to insurance liabilities, or linked to non-insurance financial variables such as NPLs and provisions. Since large natural disasters have occurred in the past, the relation between economic and financial variables can be estimated empirically, and there are some studies that have used theoretical and computational modeling to assess future damages under climate change scenarios (SFC, 2020; Zhou, Endendijk, and Botzen, 2023). It is potentially also possible to link damage estimates at an asset level in a more structural way to the value of financial assets, although we are not aware of any existing published CRST study that employs such an approach. Figure 6 depicts a typical disaster risk approach, with the top channel through insurance liabilities reflecting traditional insurance catastrophe stress tests (e.g., EIOPA, 2022).

Figure 6. Typical disaster risk approach.

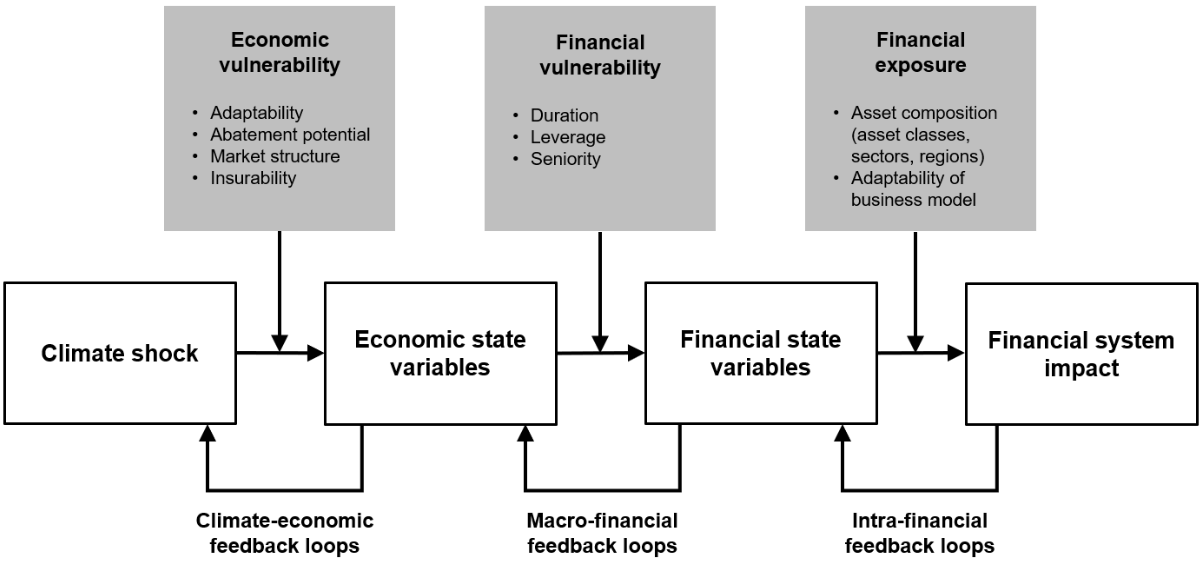


4.5 The structural form of the climate-financial relation

Part of the complexity of CRST lies in getting the functional form right regarding the propagation of climate shocks to financial sector outcomes. As shown by the complexity of the models presented in the previous sections, the shape of this relation is dependent on a range of moderating variables, which could make outcomes both context and time dependent (i.e., empirical estimates of elasticities between climate variables and financial sector variables may not be universal). The structural models that we reviewed point to several relevant moderating variables, which include firm level characteristics (such as adaptability and the potential to abate GHG emissions), market structure, financial asset characteristics (such as duration, leverage, and seniority of the instrument), and business model characteristics of financial institutions (such as asset composition and the adaptability of business models over time). Figure 7 provides a (non-exhaustive) overview.

A crucial component of the climate-financial relation are feedback loops. Figure 7 highlights the feedback loops within the financial system (intra-financial), from the financial system to the economy (macro-financial) and from the economy to climate risk (climate-economic). These feedback loops are endogenous and may amplify the initial shock, as happened during the Global Financial Crisis of 2008-2009. Current CSRT modelling approaches do not include these important feedback loops.

Figure 7 – Moderating variables in the climate-financial relation



5. CRST exercises to date

In this section we review the main system-wide CRST exercises that have been conducted to date. Most of these are conducted by central banks, financial supervisors, international organizations, and academics (e.g., Battiston et al., 2017; Vermeulen et al., 2018; Allen et al., 2020; World Bank Group, 2021; European Central bank, 2022; Hallegatte et al., 2022; Reinders et al., 2023). CRST exercises can be either bottom-up, when financial institutions make their own assessments (often using different methodologies, but similar scenarios and assumptions) after which results are aggregated, or top-down, when the assessment methodology is harmonized and data is obtained from public sources or from participating financial institutions (Ong and Jobst, 2020). Since methodologies are only harmonized for top-down exercises, we focus on this subset of all system-wide CRST exercises. We collect and compare data on scope (i.e., financial institutions and asset classes that are covered), the type(s) of climate shock assessed, modeling variables, and main outcomes. We furthermore classify each exercise according to the four modeling approaches identified in section 4 (macro-financial, micro-financial, non-structural, disaster risk) and the type of model used.

Results are provided in Table 2. All CRST exercises include banks in the analysis, with two including other financial institutions such as insurers and pension funds. More than half of the investigated studies exclusively focus either on only the loan portfolio or only the equity portfolio of financial institutions. Only Vermeulen et al. (2018) and Allen et al. (2020) assess a complete set of equity, bond, and loan portfolios using structural modeling. Jung et al. (2021) investigate the full impact of climate shocks on banks' expected capital shortfall but only use historical shocks (e.g., the fossil-fuel price collapse in 2020). By not assessing all asset classes, several studies provide partial results and hence are likely to underestimate system-wide losses in adverse climate shock scenarios. This is in particular the case for Battiston et al. (2017) who solely assess the impact on equity exposures for European banks, while more than 90 percent of assets of European banks consists of loans (Reinders et al., 2023). All top-down CRST exercises to date have assumed that balance sheet exposures remain constant during the stress test horizon.

In terms of shocks investigated, six exercises examine abrupt or sudden transition scenarios. Usually, these scenarios are operationalized by defining a carbon price path, with sharply increasing carbon prices during the assessed time horizon (for example, during the next five to ten years). Two studies investigate the impact of climate-related disasters on the financial sector (World Bank Group, 2021; Hallegatte, 2022). Furthermore, two studies investigate more gradual scenarios that unfold over a longer-term horizon, including gradual transitions and hot house world scenarios (Allen et al., 2020; European Central Bank, 2022). The financial system impact of the latter two studies is however small, chiefly because traditional financial sector stress testing typically has a time horizon of 3 to 5 years – in line with the limited duration of most debt instruments (e.g., Bolton et al., 2020). However, while climate change may be gradual, the Green Swan and Minsky-type of climate shocks would likely lead to abrupt changes in financial markets in the short term (e.g., a severe price decline of coastal assets due to news on accelerated melting of the Greenland ice sheet). To our knowledge, there are nevertheless to date no top-down CRST exercises that have assessed such scenarios. We suspect that this could be due to a lack of suitable models and difficulties in assigning probabilities to severe scenarios occurring (in order to credibly claim that these are "severe but plausible" scenarios).

Table 2 – Overview of top-down CRST exercises

CRST exercise	Scope	Climate shock	Economic state variables	Financial state variables	Financial system impact variable	Classification	Type of models used
Battiston et al. (2017)	• Banks (primarily) • Equity	Abrupt transition (full loss of value)	N/A	N/A	Fraction of portfolio exposed	Non-structural	Financial impact models (for second round effects)
Vermeulen et al. (2018)	• Banks, insurers, pension funds • Equity, bonds, loans	Abrupt transition (100 USD carbon tax)	GDP Unemployment Risk-free interest rate Equity indices (level)	Credit risk spread (bonds) Expected losses (loans)	Financial losses as percentage of total assets (between 1 and 11 percent)	Macro-financial	Macro-structural model Macro-financial (satellite) risk model Financial impact model
World Bank Group (2021)	• Banks • Loans, sovereign bonds	Abrupt transition Climate-related disaster (flood)	Sectoral value added Economic damage	Non-performing loans	Capital adequacy ratio (between – and 5 percentage points decrease)	Macro-financial Disaster risk	Computable General Equilibrium Financial impact model
Allen et al. (2020)	• Banks, insurers • Equity, debt, loans	Abrupt transition Gradual transition	GDP, inflation, unemployment (12 total)	Probability of default, market value of equity	N/A	Macro-financial	Macro-structural model Integrated Assessment Model Macro-financial (satellite) risk models
Reinders et al. (2023)	• Banks • Equity, corporate loans	Abrupt transition (100-200 EUR carbon tax)	Firm value	Market value of equity and debt	Market value losses	Micro-financial	Firm valuation model Structural credit risk model
European Central Bank (2022)	• Banks • Bonds, corporate loans	Gradual transition (disorderly) Hot house world	GDP, firm earnings and leverage	Probability of default, loss given default, bond credit spread	Expected losses	Micro-financial Macro-financial	Integrated Assessment Model
Hallegatte et al. (2022)	• Banks • Loans	Climate-related disaster (typhoon)	Economic damage Total Factor Productivity (TFP)	Earnings Market value of equity and debt NPLs	Capital adequacy ratio (between 1 and 10 percentage points decrease)	Disaster risk Macro-financial	Disaster risk model Financial impact model
Grippa and Mann (2020)	• Banks • Corporate debt	Abrupt transition	Interest Coverage Ratio (ICR) Oil revenues	Loan losses (increase of 0.8-0.9 ppt)	N/A	Micro-financial Non-structural (SVAR)	Macro-financial (satellite) risk models
Jung et al. (2021)	• Large global banks	Abrupt transition (2020 fossil-fuel price collapse)	N/A	N/A	CRISK (expected capital shortfall in climate stress scenario)	Non-structural	Non-structural empirical model

In terms of modelling, we find that there is no single comprehensive model used for CRST and, as a result, most findings are partial in nature (i.e., not covering all relevant transmission channels). In all but one CRST exercise the economic, financial, and financial institution variables are modelled in separate steps and then linked through economic and financial state variables. Given the limited number of state variables typically included in CRST exercises, it is highly likely that relevant transmission channels are omitted (for example, changes in risk-free interest rates). More integrated structural models are conceivable but, to our knowledge, have not been developed and used yet for CRST. For instance, it has been argued that Dynamic Stochastic General Equilibrium (DSGE) models can be modified to include climate change and economic and financial sector dynamics all in one model, but these models do to date not exist (Arndt et al., 2020, Anvari et al., 2022). Stacking of multiple models may furthermore increase model-error while using different models leads to lower comparability between the outcomes of different CRST exercises.

5.1 Shortcomings

Our review points to several shortcomings that need to be addressed with the further development of CRST. Taken together, these shortcomings could lead to underestimation of the impact of climate chocks on financial institution viability and hence also the potential of climate shocks to lead to financial instability. First, not all relevant climate shocks are assessed within a CRST context. For example, recent climate models indicate increasing risks of tipping points (e.g., Armstrong McKay et al., 2022). The latest science on climate shocks should be used in CRST, which implies the development of more adequate severe but plausible "green swan" scenarios beyond those provided by the traditional IAMs. Furthermore, increased attention should go to potential Minsky-type shocks emanating in the financial sector itself, if climate sentiment among investors and lenders changes suddenly. Second, CRST is highly reliant on traditional macro-financial stress testing. However, due to the asymmetric and non-linear relation between climate shocks and financial institution outcomes there is a high risk of model misspecification. Most of the traditional models discussed in this paper make strong assumptions, that are compounded when individual models are linked to each other. More granular modeling approaches should be developed that refine assumptions and provide a complementary angle to the outcome of macro-financial stress tests. Third, a fundamental shortcoming of current CSRT modeling approach is the lack of modeling feedback loops, which may amplify the impact of climate shocks. This calls for much more integrated modeling approaches, which captures better the non-linear relationship between climate, economic, and financial variables. Fourth, nearly all existing CRST exercises are partial in nature. Specifically, this relates to the limited availability of data and models to cover all asset classes (e.g., loans, bonds, and equity), all relevant risk channels (e.g., changes in risk-free interest rates and/or risk premiums), and all relevant financial institutions (e.g., banks, insurers, pension funds). This is an issue that, among others, should be addressed by improving data availability.

Table 3 – CRST shortcomings

Climate shock	Explanation
• No Green Swan and Minsky shocks	• Lack of understanding and assessment of "Green Swan" and Minsky-type scenarios
Vulnerability modeling	**Explanation**
• Overreliance on macro models	• Current climate stress testing is highly reliant on IAMs and traditional macroeconomic stress testing
• Ignoring feedback loops	• Most studies ignore feedback effects on the financial sector, economy, and climate
• Partial set-up	• Exercises are partial in nature, covering only limited sets of causal channels and asset classes

6. Conclusion and discussion

CRST is a developing field with, so far, a wide variety of approaches to model the relation between climate shocks and financial sector outcomes. Conceptually, this relation runs primarily through economic and financial state variables. We find that almost all CRST exercises follow this approach. There are however substantial differences in the type of climate shocks that are investigated (or potentially could be investigated, but have not been yet) and the way that climate, economic, and financial models are connected. We identify four types of modeling approaches: (a) traditional macro-financial; (b) micro-financial; (c) non-structural; and (d) disaster risk. We also classify climate shocks into six types: (i) abrupt transition; (ii) gradual transition; (iii) hot house world; (iv) climate-related disaster; (v) green swan; and (vi) Minsky-type. The latter two have not been investigated in any CRST exercises that we are aware of, however could be especially relevant from a financial stability perspective. Further shortcomings of CRST exercises to date include a high reliance on the traditional macro-financial approach and IAMs, the lack of modeled feedback effects, and the partial nature of the assessments (i.e., not covering all causal channels and asset classes).

We see several avenues for the future development of climate-financial modeling approaches, summarized in Table 4. First, we think it is important to develop CRST exercises that investigate the potentially most damaging scenarios (e.g., a "green swan" event or rapid repricing of financial assets). Especially from a financial stability perspective it is important to better understand unlikely but severe outcomes. Second, the next generation of climate-financial models should include feedback loops, which can amplify the impact of initial climate shocks within the economic and financial systems. Third, we suggest to further develop micro-based approaches that allow for better sectoral and spatial disaggregation. This is especially relevant for micro-prudential supervision and adequate pricing of climate-related financial risks. Fourth, disaster risk approaches could be expanded to connect catastrophe models to financial outcomes other than those for (re)insurance liabilities. This would allow disaster risk scenarios to be applied to banks and other institutional investors.

Table 4 – Avenues for future research

Climate shock
• Improve understanding of tail risks related to a changing climate (e.g. tipping points)
• Assess plausible but severe "green swan" and Minsky-type scenarios on the economy and financial sector
Vulnerability modeling
• Develop integrated modeling approaches that capture a comprehensive set of feedback loops within the financial sector, and from the financial sector to the economy and climate
• Develop microeconomic approaches to climate stress testing (to assess impacts on specific economic sectors and regions)
• Develop disaster risk stress tests for financial institutions other than insurers (building on existing disaster risk models)

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