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Climate-Related Financial Stability Risks for the United States: Methods and Applications

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OVERVIEW

- A growing body of research assesses potential U.S. climate-related financial stability risks (CRFSRs) stemming from both the transition to a low-carbon economy and the effects of physical risks.
- The authors identify ten types of models used in the literature, discussing the results generated by each as well as its strengths and weaknesses, and explore whether current modeling strategies are suitable for assessing CRFSRs.
- They find that assessments based on existing literature are subject to a high degree of uncertainty, limiting their potential role in policymaking.
- They discuss five challenges that future studies need to account for and suggest ways existing methodologies could be combined to obtain a more complete understanding of climate risks and vulnerabilities.

Policymakers are keenly interested in assessing the resilience of the financial system in relation to climate change. Such interest has led to a surge of academic research on climate change and corresponding policy options. In this article, we review the burgeoning literature on climate-related risks, focusing especially on existing methodologies that have been used to study U.S. climate-related financial stability risks (CRFSRs).

Exhibit 1 illustrates the potential transmission channels of climate-related risks to financial system vulnerabilities using the Federal Reserve Board's "risk-vulnerability" conceptualization (Brunetti et al. 2021; Board of Governors of the Federal Reserve System 2020). Physical risks can be chronic, such as droughts, or acute, such as hurricanes, floods, and wildfires. Transition risks include (1) the technological risk of certain assets losing value (becoming "stranded") as a result of green

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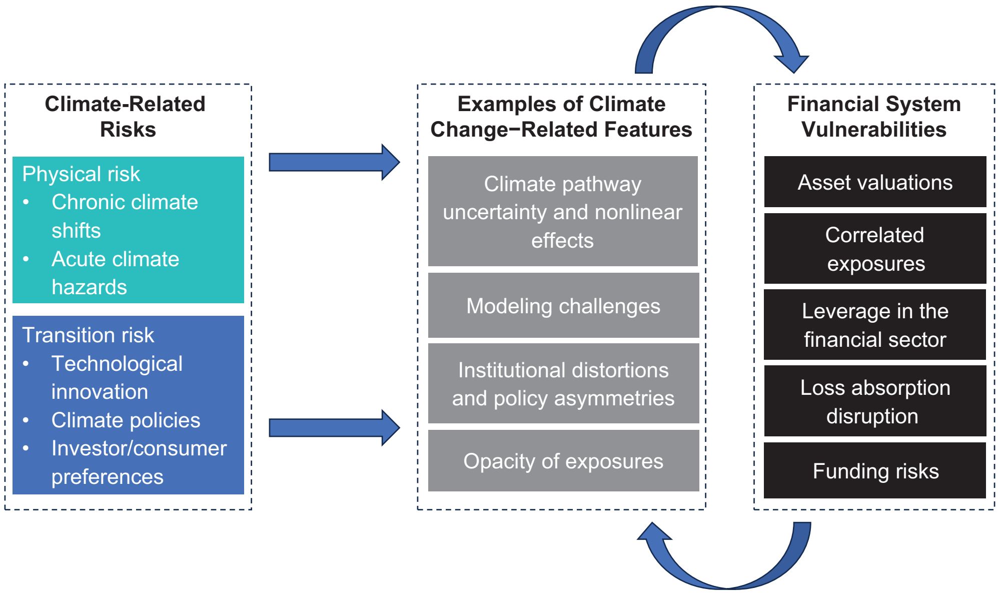
Exhibit 1
Possible Transmission Channels from Climate-Related Risks to Financial System Vulnerabilities



Note: This exhibit shows the potential CRFSRs using the Federal Reserve Board's "risk-vulnerability" conceptualization. (See Brunetti et al. 2021 and Board of Governors of the Federal Reserve System 2020.)

innovation; (2) the policy risk of induced transition to a lower-emissions economy, which raises costs to some firms, industries, and households; and (3) shifts in preferences away from carbon-intensive products. Both physical and transition risks could amplify financial system vulnerabilities as well as confound their measurement.

Although the United States has not experienced a climate-driven systemic event, it is important to study U.S. CRFSRs because many possible developments in the future could trigger systemic events and transmit risk to the U.S. financial system. For instance, the Intergovernmental Panel on Climate Change (2018) describes tipping points in the global climate system that are hard to predict, such as the loss of Arctic sea ice and widespread thawing of permafrost. Correlated risks—that is, simultaneous occurrence of multiple climate disasters—could also lead to financial stability risks in the future. For example, in 2021 alone, Texas experienced consecutive hailstorms as well as tornadoes and severe storms from April to May, multiple wildfires ravaged California, and Hurricane Ida devastated Louisiana and also caused widespread flooding in the Northeast from July to August.[1] If such climate disasters become more correlated across space and time, they might generate shocks that are large enough to induce systemic events in the future.

In this article, we identify ten classes of models that have been used to study the financial and economic effects of climate change in the United States. The literature we cover is large, new, and expanding. We examine around one hundred references, most of them written since 2020. The models used in this literature are diverse, ranging from reduced-form statistical methods to equilibrium models, input-output models, and others. Our approach to the literature is primarily methodological: we ask whether the current modeling strategies used in the literature are suitable for assessing U.S. CRFSRs. We also ask whether the literature has yet identified any significant financial stability risks for the United States stemming from climate change.

Our findings show that although both the size of the academic literature and the number of policy changes addressing climate risk have grown over the last decade, there is still surprisingly little understanding when it comes to U.S. CRFSRs. In the currently available literature on the financial and economic impacts of climate change, traditional reduced-form models are most common, followed by general equilibrium models. Outside of the academic literature, private- and public-sector entities have begun to develop or adopt scenario analysis, stress testing, and sensitivity analysis tools.

Among different types of financial system vulnerabilities, we find that the effects of climate change on asset valuations are most frequently studied in two ways. First, a body of research assesses whether sharp declines in the value of stranded assets vulnerable to climate risks pose financial stability risks. Stranded assets may generate losses for already distressed companies. Moreover, a large price shock to stranded assets used as collateral might propagate distress to the financial sector. While some studies find that climate risks are priced into real estate and bond prices to some degree, it is unclear if those risks are *fully* priced. If asset prices do not fully reflect climate risks, prices could fall sharply and create deep losses and market disruptions once the risks are realized. Second, other studies examine how the impact of climate change on the macroeconomy might have indirect effects on asset valuations (McKibbin et al. 2020). Many of the top-down methodologies covered in this article, including computable general equilibrium models, dynamic stochastic general equilibrium models, and integrated assessment models, focus on the effect of climate shocks on macroeconomic variables. However, although this type of analysis has been applied to other countries, it has yet to be undertaken for the United States (see, for example, Dunz et al. [2023]).

Our review of modeling assumptions and results shows that currently available insights should be interpreted with caution, since the literature remains relatively thin (Cartellier 2021). We conclude that assessments based on the existing literature are subject to a high degree of uncertainty, limiting their potential role in policymaking. This is not a criticism of the literature taken on its own terms. Many papers are careful to stress the limits of their analyses and to emphasize the early nature of the climate and finance literature. Some authors, such as Barnett, Brock, and Hansen (2021), are making progress in developing approaches that allow for quantitative analyses in the presence of model ambiguity and misspecification. Others are expanding the set of interactions between policy domains, including monetary, distributional, and carbon tax policies, among other things (Känzig 2023; Del Negro, di Giovanni, and Dogra 2023), or the integration of highly disaggregated data (Bilal and Rossi-Hansberg 2023).

Based on our findings, we discuss five unique challenges of assessing climate risks and climate vulnerabilities that future studies need to account for: (1) uncertainty surrounding climate change, (2) long time horizons, (3) heterogeneous risk effects, (4) technological progress, and (5) the modeling of damage functions to measure the economic effects of climate change.

We also provide suggestions on how existing methodologies could be combined for a more complete understanding of CRFSRs. For example, the reduced-form outputs from micro- and macroeconometric statistical methods can be used to inform the main parameters and assumptions in general equilibrium models, as well as the distributions of different random variables in agent-based models. In turn, equilibrium models and agent-based models can be used to design constructs that feed into scenario analysis, stress testing, sensitivity analysis, and other approaches.

Some methodologies are particularly promising for future research. Although not yet used in the literature to assess U.S. CRFSRs, a combination of computable general equilibrium models, input-output models, agent-based models, and statistical methods seems particularly promising. These models can overcome some, if not many, of the challenges of climate risk modeling. For example, computable general equilibrium models might potentially be used to analyze the effects of climate events and policies on the balance sheets of businesses and households, flexibly broken down at the regional and/or sectoral levels. And while input-output models are simpler, they take into account the interlinkages among different sectors in the economy. Agent-based models can capture complex interactions and feedback mechanisms between heterogeneous agents and the financial and real sectors of the economy.

The rest of this article is organized as follows. In Section 1, we review the methodologies currently used in the literature to assess climate-related risks. We discuss the insights generated by each methodology as well as its relative strengths and weaknesses. (The Appendix contains a brief description of the data needed for each methodology.) In Section 2, we discuss how these models can be further developed or combined to assess U.S. CRFSRs and include suggestions for future research. We conclude the article in Section 3.

1. Methodologies to Assess Climate-Related Risks

In this section, we discuss the methodologies that have been used to study climate-related risks and that could be further employed to analyze U.S. CRFSRs. We briefly describe each methodology, explain how it has been used in the literature, and present its key empirical findings. We discuss statistical methods in Section 1.1, general equilibrium models in Section 1.2, additional methodologies in Section 1.3, and supervisory and practitioner approaches in Section 1.4. In the Appendix, we provide a brief description of the data needed for each methodology.

1.1 Statistical Methods

Macro- and microeconometric statistical methods have been used in asset pricing and corporate finance to identify and measure U.S. CRFSRs. The asset pricing literature analyzes whether physical and transition risks are incorporated in the prices of financial assets, including equity, fixed income, and real estate assets. The corporate finance literature analyzes the extent to which firms, and the production sector at large, are exposed to physical and transition risks. These two types of analyses are informative for U.S. CRFSRs because, through its asset holdings, the financial sector is exposed, directly and indirectly, to (1) dislocations in asset prices—for example, driven by unexpected shocks such as a tighter-than-expected transition policy, as in Bauer, Offner, and Rudebusch (2023), or reassessments of physical and transition risks, among others—and (2) direct and indirect losses originating from exposures to corporations affected by climate events.

The literature relying on statistical methods provides evidence of changes in banks' and firms' behavior in response to physical risk. Brown, Gustafson, and Ivanov (2021) show that firms respond to winter weather by drawing down and increasing the size of their credit lines with banks. Meisenzahl (2023) finds that banks reduce lending to counties facing increased disaster risk, particularly for riskier loans and borrowers. Kacperczyk and Peydro (2022) find that banks with stronger decarbonization commitments reduce lending to firms with larger carbon footprints. Ivanov, Macchiavelli, and Santos (2022) show that banks help firms hit by disasters but reduce their credit supply to distant regions that are not affected by disasters. Correa et al. (2022) provide evidence that, following disasters, banks increase rates charged to at-risk firms, but not to unaffected firms. Barth, Sun, and Zhang (2019) and Blickle, Hamerling, and Morgan (2021) document that bank income increases after natural disasters, and that physical risks to banks are modest. The latter also find increased lending after weather disasters, with only small effects on loan losses and default risk. By contrast, Noth and Schuwer (2017) find that extreme weather events increase the likelihood of banks' default and raise banks' foreclosure rates. Keenan and Bradt (2020) show that lenders, in the aftermath of natural disasters, are more likely to approve mortgages that can be securitized, thereby transferring climate-related risks. Finally, Oh, Sen, and Tenekedjieva (2022) find that insurers cross-subsidize protection contracts from unregulated states to states with a rate regulation.

The statistical methods literature also speaks to the effects of physical climate risks on asset prices. Baldauf, Garlappi, and Yannelis (2020) and Bernstein, Gustafson, and Lewis (2019) analyze the effect on real estate prices. These papers find that increases in sea levels significantly affect house prices, which, in turn, affect the values of real estate–related assets on the balance sheets of financial institutions. Huynh and Xia (2021) find that prices of corporate bonds incorporate climate-related risks. Goldsmith-Pinkham et al. (2022) and Schwert (2017) show that municipal bond prices incorporate climate-related risks to some degree, and Braun, Braun, and Weigert (2021) find a "hurricane premium": stocks with a low sensitivity to U.S. hurricane losses outperform those with a high sensitivity. Finally, Acharya et al. (2022) find that heat stress is priced across various asset classes, and Kruttli, Tran, and Watugala (2023) document that the implied volatility of firms' options increases substantially after a hurricane, suggesting an effect on the pricing of uncertainty.

Statistical models have also been used for prediction, risk management, and stress testing. Lemoine (2021) estimates that an additional 2°C of global warming would eliminate profits from farmland in the eastern United States. Rao (2017) finds that the predicted sea level rise from now to 2100 would cause almost 300 U.S. cities to lose at least half of their residential real estate, and Hauer, Evans, and Mishra (2016) find that such a rise in sea level would place 4.2 million people at risk of inundation. Using data from financial markets, Engle et al. (2020) present a methodology for constructing portfolios that hedge climate-related risk using publicly traded assets, and Perez-Gonzalez and Yun (2013) show that weather-sensitive firms would greatly benefit from the introduction of weather derivatives. Alekseev et al. (2022) provide evidence of how investors can exploit information on mutual fund trading after reassessments of climate risk to construct successful hedge portfolios. Finally, Curcio, Igor, and Vioto (2023) provide a comprehensive analysis of the exposure of U.S. banks and insurers to climate risk, and Gourdel and Sydow (2022) present a stress-testing framework for investment funds.

In sum, the literature suggests that both housing and securities markets are vulnerable to physical risks and changes in individual beliefs about climate change. This assessment of vulnerabilities linked to physical risk is mostly driven by commercial and residential real estate, through direct holdings and securitization activity.

Statistical models also analyze how firms and investors respond to transition risks. One strand of the literature documents how transition risk is priced into financial assets. Hsu, Li, and Tsou (2023) document a large pollution premium—that is, substantially higher returns generated by firms with high toxic emissions intensity. Similarly, Baker et al. (2020) show that investors sacrifice returns to hold municipal green bonds, and Chava (2014) finds that investors demand significantly higher expected returns on stocks excluded by environmental stock screens (such as hazardous chemical and substantial emissions). Kolbel et al. (2022) show that risk disclosures can either increase or decrease spreads on credit default swaps, depending on whether the disclosure reveals new risks or reduces uncertainty. Pastor, Stambaugh, and Taylor (2022) find that green stocks typically outperform brown stocks when climate concerns increase, and Seltzer, Starks, and Zhu (2022) document that firms' bond-financing costs reflect carbon footprints. Finally, Bolton and Kacperczyk (2021) analyze firms' exposures to carbon transition risk, documenting higher stock returns for companies with higher levels of carbon emissions.

The literature has also shown how financial institutions, and banks in particular, react to transition risks in their portfolio choice. Using syndicated loan data, Ho and Wong (2023) show that banks started to price transition risks into their loan offerings after 2015. Ivanov, Kruttli, and Watugala (2022) show that high-emissions firms face shorter loan maturities, higher interest rates, and lower access to bank financing compared to low-emissions firms. Chava (2014) shows that lenders charge a higher interest rate on loans issued to firms with environmental concerns, and Mueller, Nguyen, and Nguyen (2022) show that banks tend to securitize loans to offload part of their transition risk when borrowers increase the intensity of their carbon emissions. In contrast, Mueller and Sfrappini (2022) document that U.S. banks reallocate credit to firms at risk of being affected by regulatory interventions. In the context of the insurance sector, Jung et al. (2023) document a positive association between larger exposures to risky states and higher holdings of brown assets with higher sensitivity to physical and transition risk. Building on estimated sectoral effects of climate transition policies from general equilibrium models, Jung, Santos, and Seltzer (2023) find that carbon emissions can explain at most 60 percent of bank exposures estimated from general equilibrium models. Finally, Jung, Engle, and Berner (2021, revised 2023) quantify a measure of banks' capital shortfall in a climate stress scenario called "CRISK"—climate risk exposure—and find that U.S. banks' exposures to transition risks are manageable.

A few other studies predict how firms and the public sector react to transition risk and the adoption of environmental policies. Specifically, Bartram, Hou, and Kim (2022) document that, in response to localized green policies, firms increase their pollution in nonregulated states, and Morris, Kaufman, and Doshi (2021) document that the transition from carbon is likely to adversely affect the public finances of coal-dependent communities.

In sum, the literature suggests that both nonfinancial and financial firms are vulnerable to transition risk, implying that if investors were to reassess this risk, asset prices could change suddenly. While physical risk tends to be geographically clustered, transition risk is inherently more industry-specific. Although small financial institutions tend to be less geographically diversified (and thus more exposed to physical risk), larger financial institutions are likely to be better geographically diversified. However, large institutions may still potentially specialize in lending to some industries (Blickle, Parlatore, and Saunders 2021), thus exposing themselves to transition risk.

Limitations and discussion. While the literature relying on statistical methods is relatively abundant, its findings are subject to substantial uncertainty. Given their partial equilibrium and inherently backward-looking nature, these models can be used to measure correlations in past data and to discipline equilibrium models. However, the estimated coefficients typically depend on an empirical setting, such as a specific natural event, that may not be broadly representative. Thus, the magnitudes obtained with statistical methods might not generalize outside the empirical context in which the methods are applied sufficiently well to guide policy.

Statistical methods are intuitive, simple to estimate, and able to capture the important role of heterogeneities (for example, geographic, sectoral, or regulatory) for assessing CRFSRs. They also complement equilibrium frameworks by allowing researchers to quantify parameters and by documenting the correlations that these models need to generate. But they require detailed and granular data that are not broadly available for many applications, and they rely on partial equilibrium models estimated on past or current information that may not be informative about future trends. Hence, statistical models ignore equilibrium considerations that are particularly important given the long time-horizon of climate change and the role of technological change, among other things. While well suited to estimating direct damages, these models, because of their reduced-form nature, do not generate a precise estimate of the indirect costs, such as social costs. Moreover, statistical methods do not necessarily capture the inherent uncertainty of climate change. Nonetheless, they can be helpful in documenting historical nonlinearities of physical and transition risks. It should also be noted that statistical methods can be used to develop climate scenarios that serve as inputs for other approaches.

1.2 General Equilibrium Models

General equilibrium models solve a complex nonlinear system of endogenous responses and systemic interactions of economic agents and sectors in the economy, generating internally consistent economic outcomes that incorporate the crucial role of prices and markets. In climate studies, general equilibrium models can therefore go beyond reduced-form or statistical methods and provide a useful benchmark for how the real sector is likely to respond over time to changes in prices, demand, and supply generated by climate change. In this section, we discuss two of the most popular general equilibrium models: computable general equilibrium models and dynamic stochastic general equilibrium models.

Computable general equilibrium models

Computable general equilibrium (CGE) models are widely used to computationally solve for key economic equilibrium outcomes, including resource allocation and income distribution, in a theoretically consistent fashion. In climate studies, CGE models have proven useful in estimating the magnitudes of disruptions in economic activity under different climate scenarios, and the ensuing economic outcomes and welfare effects, allowing for comparative statics analyses.[2] The materialization of physical climate risks has been known to cause substantial economic losses, as measured in terms of various outcomes including industrial-sector outputs and the supply of human capital (see Fan and Davlasheridze [2019] and Rose and Liao [2005], among others). Moreover, CGE models have found significant and pervasive general equilibrium effects—measured by macroeconomic variables such as consumption, the capital stock, and labor supply—arising from transition risks (see, for example, Babiker et al. [2000]; Hazilla and Kopp [1990]; and Jorgenson and Wilcoxen [1993]). However, to date, CGE models have not been used to study the effects of physical or transition risks on U.S. financial stability.

Limitations and discussion. One of the biggest weaknesses of CGE models is the "black box" aspect—referring to complex and often custom-written models with a large number of variables—which makes it hard to disentangle causal mechanisms and trace the effects of policies on particular features or parameters of the model. CGE models are also criticized for having strong assumptions about perfect information and exogenous technology, a lack of adjustment costs in production, and an inelastic labor supply. These strong assumptions do not allow CGE models to address uncertainty, input substitution, or endogenous responses in technology. Nevertheless, by sacrificing the modeling of uncertainty and endogenous mechanisms, CGE models eliminate computational challenges and are therefore more amenable to handling higher degrees of cross-sectional heterogeneity. CGE models can be flexibly adjusted to multisector, multicountry, or global setups, each of which is suitable for assessing policies covering different jurisdictions.

CGE models have two particularly promising possibilities for future studies. First, these models have significant potential to inform researchers and policymakers about the effects of climate events and policies on the balance sheets of businesses and households, and they can provide flexibility in disaggregating the analysis at the regional and sectoral levels. And because CGE models can be easily adapted, they can be used to quantify the effects of climate change on banks' credit risk. For example, estimates of businesses' and households' losses from physical or transition risks can be used to inform potential changes in debt and leverage by nonfinancial businesses and households. These changes can then ultimately predict changes in credit risk and delinquency/defaults on corporate loans, mortgages, auto loans, and other loans. Similar estimates can be used as inputs for stress test models and scenario analyses.

Second, CGE models can be designed to incorporate both climate and financial sector components. Some academic and empirical studies include climate change in CGE models. However, in only a few cases do CGE models include financial intermediation (see Diaz-Gimenez et al. [1992] for a CGE model with a banking sector), partly reflecting the computational challenge in incorporating agent heterogeneity into a standard CGE model. Computational developments, however, should help to solve this issue, and a CGE climate model that accounts for financial intermediation would be valuable for examining U.S. CRFSRs.

Dynamic stochastic general equilibrium models

Similar to CGE models, dynamic stochastic general equilibrium (DSGE) models constitute another type of micro-founded general equilibrium model that incorporates behavioral changes and systemic interactions among agents and sectors in the economy. The distinction between DSGE and CGE models is that the former can partially account for uncertainty and endogenous changes in technological innovation. These two factors are critical to our understanding of climate change.

The academic literature using DSGE models to study U.S. CRFSRs is newly emerging. Barnett (2023) proposes a DSGE model to examine the asset pricing implications of physical climate risks and uncertainty. Specifically, the model incorporates uncertainty about climate risk into the climate model and examines how these features affect asset prices. Barnett (2023) finds that accounting for uncertainty amplifies the effect of climate change on the climate risk premium and requires an increasingly positive risk premium as climate change progresses. The implications are largely consistent with findings from the empirical climate finance literature on the valuation impacts of climate change.

Carattini, Heutel, and Melkadze (2021) study how transition risks, in response to a carbon tax, can threaten the stability of the banking system. Their DSGE model includes a banking sector and a moral hazard problem between depositors and banks. Calibrated on U.S. data, simulations over a five-year horizon show that an abrupt transition can induce banking sector volatility by causing bank capital to fall by around 10 percent via bank exposures to the assets of polluting firms.

In addition to the emerging literature, another way that DSGE models inform financial stability risks is through the estimation of economic effects of climate-related risks, which, in turn, have been increasingly used by central bankers and industry practitioners to develop climate scenarios. These scenarios feed into macro-financial and macroprudential analyses such as stress tests, which support climate-related policy analysis, and forecasting. Many DSGE models used in climate studies, including those referred to as environmental DSGE (E-DSGE) models, have been widely used to study the economic effects of climate-related risks in the United States and to explore optimal policy responses (see Keen and Pakko [2011], Fischer and Springborn [2011], Heutel [2012], Golosov et al. [2014], Annicchiarico and Dio [2015], Dissou and Karnizova [2016], and Van den Bremer and Van der Ploeg [2021], among others).

Limitations and discussion. Overall, the growing literature on E-DSGE models will help researchers examine the dynamic interactions between the real and the financial sectors, which, in turn, will provide valuable insights into the financial stability implications of climate risks. However, DSGE models are not without their own challenges. Incorporating uncertainty and endogenous technology limits the size of a typical DSGE model and restricts the number of details the model can handle. For example, current DSGE models are limited in their ability to incorporate disaggregation across sectors and jurisdictions, heterogeneous climate exposures by different economic agents, and richness in climate damage functions. Strong assumptions about rational expectations and the stationarity of fundamentals are also commonly criticized features of DSGE models. The stationarity assumption is particularly restrictive for climate studies because errors may significantly compound over time.

1.3 Additional Methodologies

Although the academic literature addressing climate risk has gained momentum over the last decade, surprisingly little information is available on U.S. CRFSRs beyond studies using statistical methods and some of the general equilibrium models described in the previous sections. In this section, we briefly present additional methodologies that are used either to measure the economic (but not the financial stability) effects of climate risk in the United States, or to assess CRFSRs in a foreign country. Specifically, we discuss the literature on integrated assessment models, input-output models, overlapping generations models, and agent-based models.

Integrated assessment models

The term integrated assessment models (IAMs) refers to a group of models that combine economic and climate "modules" to conduct a highly aggregated cost-benefit analysis of climate change mitigation or to analyze the cost-effectiveness of climate policies and resulting emissions pathways. The economic module is based on a partial or a general equilibrium model, akin to those described above but, most often, in simpler and highly aggregated forms. The climate module models greenhouse gas emissions and the carbon cycle, and estimates the changes to incremental geophysical factors such as global mean temperature.[3]

To the best of our knowledge, current IAMs do not model financial intermediation and thus have not been used to study U.S. CRFSRs arising from physical or transition risks. Instead, IAMs are used to find broad economic implications of climate change and build integrated economic and climate scenarios. IAMs are featured prominently in reports from the Intergovernmental Panel on Climate Change and are used by many government agencies to calculate the social cost of greenhouse gas emissions (Interagency Working Group on Social Cost of Greenhouse Gases 2021). Several stress tests and scenario analyses rely on a set of scenarios constructed using IAMs.

Limitations and discussion. IAMs tend to be highly aggregated in order to tame the computational challenges of combining multiple modules, and adding a financial sector module would necessarily entail greater complexity. In particular, the representative agent approach used in most IAMs may need to be altered to incorporate financial agent heterogeneity to be useful. The same modeling and computational complications apply to incorporating long-term technological advancements or damages from disorderly transitions away from fossil fuels. The lack of robustness will also remain a problem, unless researchers find ways to improve IAMs' ability to address uncertainty about climate sensitivity and reduce arbitrariness in parameterization and damage functions. IAMs' simplistic damage functions, which are central to their use for cost-benefit analysis, have been heavily criticized by researchers (see, for example, Pindyck [2017] and Farmer et al. [2015]).

Input-output models

Input-output (IO) models are quantitative economic models that incorporate interdependencies between different sectors of an economy. They show how the output from one industrial sector may become an input to another sector. Thus, these models help identify not only industries that produce carbon-intensive assets, but also industries using such assets as inputs. Because indirect losses from a climate event may surpass direct losses in a developed and highly interconnected economy, IO models have gained interest, especially in evaluating disasters.

To date, no study has been conducted that employs IO models to assess U.S. CRFSRs arising from transition or physical risks. That said, a few papers study the effects of transition risk on financial stability at an international level; see Vermeulen et al. (2018) for an application in the Netherlands and Mainar-Causapé, Barrera-Lozano, and Fuentes-Saguar (2020) for an application in various European Union countries.

Furthermore, a few studies use IO models to assess the economic effect of climate risks and policies in the United States and abroad. Mathur and Morris (2014) and Marron and Toder (2015) examine the distributional effects of a carbon tax across income classes and regions in the United States. Hallegatte (2008) and Kunz et al. (2013) study the socioeconomic costs of Hurricane Katrina and Hurricane Sandy, respectively. Besides estimating fatalities and direct losses as a result of hurricanes, the authors use a sector-specific IO model to estimate the indirect losses. The U.S. Environmental Protection Agency developed another application of the IO models: the U.S. Environmentally-Extended Input-Output (USEEIO) model (Yang et al. 2017). USEEIO uses IO tables produced by the Bureau of Economic Analysis and pairs them with environmental data on resource use and releases of pollutants from various public sources. The model's output can be used to quantify the environmental impact of all commodities and industries in the United States. Carvalho et al. (2021) quantify the role of input-output linkages in amplifying physical shocks to supply chains and, in turn, to the overall macroeconomy by using the Great East Japan Earthquake of 2011 as an exogenous shock. Similarly, Barrot and Sauvagnat (2016) study the propagation of firm-level idiosyncratic shocks in production networks following natural disasters.

Limitations and discussion. The most important caveat of these models is their mostly backward-looking nature and their reliance on extrapolation from past trends, since they rely on historical input-output tables. As a consequence, these models cannot capture significant technological advances and are more relevant for analyses with short- to medium-term horizons rather than more climate-appropriate longer-term horizons. In addition, IO models mainly focus on supply chain disruptions, rather than general equilibrium effects, and thus arguably capture only partial effects.

However, we believe there is room for IO models to be employed to assess U.S. CRFSRs. The main strength of these models lies in their ability to provide a simple and robust method for evaluating the linkages among different sectors in the economy. Since these models rely on IO data, they do not require strict assumptions and are helpful for addressing the uncertainty inherent in modeling climate change. IO models are less complex than many alternatives, such as CGE models. By construction, they incorporate heterogeneous agents into the economy (at least at the sectoral level) and might be useful in identifying geographies and sectors potentially vulnerable to transition policies. Finally, IO models are useful for producing estimates of climate-change-related damages by incorporating linkages among different sectors.

Overlapping generations models

In contrast to the infinitely lived agents in equilibrium models, overlapping generations (OLG) or life-cycle models are populated by cohorts of agents that coexist for some finite period. This intergenerational feature, typically with "young" and "old" cohorts, makes the models particularly instructive because the costs and benefits of climate change and mitigation policies fall unevenly on different generations. OLG models can also capture externalities and dynamic inefficiencies that may result if current generations do not consider how their decisions affect future generations. To the best of our knowledge, none of the OLG literature to date considers the financial stability implications of physical or transition risks for the United States.

Limitations and discussion. An early contribution by Howarth (1998) calibrates an OLG model of climate change to study optimal abatement policies under alternative social welfare functions. More recently, Rausch and Yonezawa (2018) and Williams et al. (2014) use an OLG framework to analyze the distributional effects of carbon taxes. While useful in those regards, the OLG framework as applied in the climate context tends to be theoretical (or, occasionally, simulated), so it may be less useful than other methodologies for calibrating CRFSRs.

Agent-based models

Agent-based models (ABMs) are simulation-based models that capture complex interactions and feedback mechanisms between heterogeneous agents and the financial and real sectors of the economy. Agents can be households, firms, banks, and the government, among other entities, and ABMs are flexible enough to model detailed characteristics for each agent. This allows for a more realistic representation of socioeconomic and financial systems. This granularity is beneficial because the effects of climate-related risks are highly disparate (see Hsiang et al. [2017]).

Another modeling advantage of ABMs for climate-related analysis is that they can incorporate empirical evidence (since they are not equilibrium constrained) and thus have more realistic damage functions compared to other modeling techniques. Furthermore, ABMs can incorporate uncertainty in agents' decision-making and capture endogenous changes that arise due to agent interactions, such as the adoption of technology or the formation of market structures. ABMs can also partly address some of the uncertainties unique to climate change modeling—for instance, tail risks and climate tipping points—since they inherently run repeated simulations for events associated with different probability distributions. These advantages make ABMs promising for climate-related analysis, especially considering that they can be used to forecast outcomes over longer time horizons.

However, to the best of our knowledge, ABMs have not yet been used to study U.S. CRFSRs, either physical or transition risks, but a strand of the literature employs ABMs to study the economic effects of climate-related risks and interactions between domestic and international climate policies (see Botte et al. [2021], Czupryna et al. [2020], Gerst et al. [2013], and Lamperti et al. [2018]).

Limitations and discussion. Despite the merits of ABMs, their results are still subject to uncertainty and do not fully capture the costs and risks of climate change because agents' behaviors may not be rational and representative with respect to climate-related risks (Farmer et al. 2015). Additionally, ABMs are computationally very intensive and require detailed data to build agents' behavioral rules (see Farmer et al. [2015] and Patt and Siebenhüner [2005]). However, as computing power increases and socioeconomic and climate data sets expand, these challenges may become less relevant.

Overall, we believe ABMs are particularly well-suited for studying U.S. CRFSRs. Researchers can closely simulate financial market structures by programming agents to operate in networks interacting with each other. Such granular specifications can help identify which agents are more vulnerable to climate-related risks, how significant their exposure is, and what risk-amplification mechanisms exist. For example, in an ABM, a researcher could introduce a policy shock such as a carbon tax and assess how it may lead to defaults among banks with carbon-intensive assets. By incorporating fire sales, researchers could study the effects on the financial positions of other banks holding overlapping portfolios, thus analyzing the financial stability of the system. Given the interconnectedness of the financial system, the model could be expanded to include foreign banks to capture spillovers from climate-related shocks abroad. As another example, a researcher could build an ABM with households and the government as agents to gauge how changes in federal policy—for example, an increase in National Flood Insurance Program (NFIP) premiums—may affect households' decision-making and consumption choice sets. A researcher could then introduce banks as agents to assess how these impacts could affect the valuation of certain assets on their balance sheets, such as residential mortgage-backed securities. Again, by building networks across banks and introducing fire sales, a researcher can study how NFIP pricing changes could affect the financial stability of the system.

1.4 Supervisory and Practitioner Approaches

In this section, we discuss methodologies that have been developed and adopted outside of the academic literature and that are widely used in the private and public sectors, including by regulators. These methodologies include (1) scenario analysis, stress testing, and sensitivity analysis, (2) climate risk scores and ratings, (3) climate value-at-risk, and (4) natural capital analysis.

Scenario analysis, stress testing, and sensitivity analysis

Scenario analysis, stress testing, and sensitivity analysis are methodologies that assess financial and economic conditions under different climate scenarios over a longer-term horizon. These scenarios take differing projected levels of greenhouse gas emissions, temperature increases, climate action policies, technological change, and damages to the global economy, among other things, as inputs to project financial and economic impacts, such as fluctuations in real estate prices. Scenarios can be created using the methodologies discussed in this article, such as IAMs and statistical methods, but researchers typically use "off-the-shelf" scenarios developed by economists and climate scientists for the public research community. Examples include the representative concentration pathways (RCP) scenarios and those published by the Network of Central Banks and Supervisors for Greening the Financial System (NGFS) and the International Energy Agency (IEA).

Scenario analysis is a broad category of studies, while stress testing and sensitivity analysis are more specific and therefore differ slightly in construction and applicability. In a climate stress test, a modeler might use granular balance-sheet data to estimate the impact of tail events—such as multiple Category 5 hurricanes affecting the East Coast over a short time frame—on a large financial institution's portfolio (a microprudential exercise) or the financial system as a whole (a macroprudential exercise). See Acharya et al. (2023) for a review of the design of climate stress tests to assess the exposure of the financial sector to macroprudential risks from climate change. In a sensitivity analysis, one parameter is changed between two scenarios to analyze its specific effect. For example, given a carbon tax scenario, a sensitivity analysis might change the parameter for the cost of renewable energy technologies to gauge how sensitive the prices of renewable alternatives are to the policy change.

Practitioners have widely employed scenario analysis, stress testing, and sensitivity analysis to study the impacts of physical risks.[4] Three examples include: (1) The UBS Group conducted a sensitivity analysis as part of the United Nations Environment Programme Finance Initiative (UNEP FI) pilot to estimate the exposure of UBS's utility company loans to the incremental physical damages of climate change, translating productive capacity losses into probabilities of default under competing climate pathways (United Nations Environment Programme 2018); (2) Citibank conducted a scenario analysis exercise to assess the operational resiliency of two large employee centers in New York City and Tampa in the event of simultaneous severe thunderstorms and tropical storms, finding that remote work strategies can maintain business continuity (Citigroup 2020); and (3) McKinsey conducted a case study examining the impacts of storm surges on residential real estate in Florida, and projects that losses from tail events are likely to increase from about \$35 billion today to \$50 billion by 2050 (McKinsey Global Institute 2020).

These methods have also been used to understand the potential for transition risks to financial institutions, including the impact of a sudden change in climate-related policies and regulations or the long-term impact of changes in production and consumption related to the transition away from carbon-intensive activities. The California Department of Insurance and the New York Department of Financial Services partnered with the 2° Investing Initiative to analyze exposures of insurers to transition risk using scenario analysis (California Department of Insurance and 2° Investing Initiative 2018; New York Department of Financial Services and 2° Investing Initiative 2021). These studies reveal that the forward-looking five-year plans of most firms do not align with the Paris Agreement and highlight within-industry differences in exposure to carbon-intensive sectors.

Among central banks, the European Central Bank (ECB) and the European Systemic Risk Board (ESRB) conducted a long-term scenario analysis exercise using three different NGFS scenarios to identify climate-related financial stability vulnerabilities and physical and transition risks at the country, sector, and firm level. The ECB also conducted an economy-wide climate stress test to assess the resilience of 4 million nonfinancial corporates and 1,600 euro-area banks to physical and transition risks under NGFS scenarios over a thirty-year forecast period. A key strength of their analysis was the construction of an extensive data set that merged firm-level financial data and climate-related risk data (including physical risk scores and carbon emissions data) with data on banks' exposures through loan and corporate bond holdings. These granular data allowed the ECB to pinpoint physical and transition risks at the sector, bank, and country level and to compute loan portfolio default probabilities for firms and banks.

De Nederlandsche Bank (DNB) conducted an energy transition risk stress test in 2018 that assumed significant emissions reductions to better understand the potential financial stability implications of a disorderly transition. The exercise used four severe but possible energy transition scenarios over a five-year forecast period to ensure that financial institutions have relevant short- to medium-term resilience. In this analysis, the DNB also used detailed data on securities holdings to determine most of the equity and bond exposures of banks, insurers, and pension funds.

The Bank of England (BoE) undertook its first financial system climate stress test (the Climate Biennial Exploratory Scenario) in 2021 to assess the risks posed to the largest U.K. banks and insurers. In this exercise, the BoE explored three scenarios that implemented a carbon pricing policy to achieve the U.K.'s stated 2050 net-zero objectives, but at differing speeds of implementation.

Finally, the L'Autorité de Contrôle Prudentiel et de Résolution and the Banque de France assessed the implications of physical and transition risks for credit, market, and sovereign risks for nine banks and fifteen insurance institutions using NGFS scenarios. The exercise introduced important methodological innovations, such as dynamic balance-sheet assumptions and investment in and out of sectors based on climate-related risk-reward considerations by financial institutions.

Limitations and discussion. A key benefit of scenario analysis, stress testing, and sensitivity analysis is that they can address some of the uncertainties inherent in climate-related risks by considering a wide range of possible future pathways, instead of attempting to predict an exact future outcome. Additionally, these methods are applicable to many institutions, such as banks, governments, insurers, and central banks, for purposes such as risk management, strategic decision-making, investment in climate adaptation needs, and resource allocation. This wide-ranging applicability may shed light on heterogeneities in climate-related risks.

Despite their wide applicability, these methodologies have some limitations as well. First, results are unlikely to fully capture the interconnectedness of the financial system because off-the-shelf scenarios do not incorporate interconnectedness within the scope of their construction. For example, the ECB/ESRB exercise uses NGFS scenarios and does not explicitly account for amplification channels such as fire sales. To overcome this challenge, researchers can make additional assumptions to connect climate-related data and financial impacts, as noted by the NGFS.[5] For example, if a hurricane were to devalue coastal real estate in Miami, firms holding assets tied to that collateral might need to sell other assets at discounted prices to cover losses. Such a fire sale would negatively affect another firm holding a similar portfolio and could potentially prompt a liquidation spiral. To capture these cascading financial system effects, a modeler could introduce assumptions to connect balance sheets across firms.

Second, their results are still subject to uncertainty and hampered by gaps in the data. Regulators rely on historical data to inform their understanding of potential future risks. However, historical records may be incomplete or of little use for predicting the severity and frequency of future climate disasters.

Finally, there remains a lack of detailed financial and climate data, making it difficult to aggregate institution-level data on, for instance, firms' Scope 1, 2, and 3 emissions.[6] This was a key takeaway from the Bank of England's exercise. Participants lacked the data needed to manage risks, so heterogeneous approaches were taken across organizations to assess and model risks. Policies that standardize global climate disclosures could alleviate such challenges.

In a critical review of climate stress testing, Cartellier (2021) addresses these and other criticisms of the current state of climate stress testing and suggests two ways forward. First, she argues for the complementary use of short-term hypothetical scenarios in conjunction with the long-term NGFS scenarios. The richer set of interactions that can be validly imposed over shorter time horizons should allow for introducing decision-making under uncertainty (as opposed to the "perfect foresight" assumptions typically used for financial participants). Second, she promotes "reallocation strategy tests" as a means of capturing the feedback from risk to financing and back to risk (otherwise known as the principle of double materiality; see Gourdel et al. [2022]).

Climate risk scores and ratings

Climate risk scores and ratings offer insights into how entities may be exposed to climate-related risk at the asset, portfolio, institution, and regional levels based on current firm characteristics. Multiple private and public entities offer these assessments, and these metrics can be used in conjunction with other methodologies, such as scenario analysis.

Climate risk scores and ratings usually do not analyze physical and transition risks separately; these metrics quantify exposure to both types of risks in a single measure. That said, Bank of America has conducted a pilot project to estimate the physical risk exposure of a sample of their U.S. residential mortgage holdings (Bank of America 2020). The project assigned a score to each property based on how severely it may be affected by twelve types of hazards and how a given hazard may affect the remaining value of the mortgage. These risk scores were then used to visualize the bank's potential risk exposure across the United States.

Limitations and discussion. A drawback of this methodology is that the providers of scores and ratings employ different, undisclosed methodologies, making comparison difficult. Indeed, Pelizzon, Rzeznik, and Hanley (2021) find that disparate environmental, social, and governance (ESG) scoring may inadvertently lead investors to trade stocks under mistaken perceptions of ESG compatibility, with implications for asset pricing and financial stability. Additionally, scores and ratings might not accurately reflect the true sustainability. For example, ESG scores are shown to positively correlate with high carbon emissions (Boffo et al. 2020). Berg et al. (2022) develop a noise-correction procedure to better understand how ESG performance affects stock returns. Given the lack of transparency, quality, and comparability, further research is needed to improve climate risk scores and ratings.

Climate value-at-risk

Climate value-at-risk (CVaR) analysis applies the traditional value-at-risk framework to assess the effects of climate change on the financial system. Using this methodology, researchers can estimate the value of financial assets at risk at a given probability over a particular time horizon for multiple climate scenarios, which can be derived from IAMs, CGEs, DSGEs, or statistical methods.

The CVaR literature and data examining physical and transition risks are sparse but slowly expanding. Ceres (2021) examined the CVaR of the syndicated loan portfolios of major U.S. banks and concluded that the CVaR related to physical risk is about $250 billion. Ceres' analysis relies on shared socioeconomic pathways scenarios and also uses a CGE model to estimate indirect effects. Similarly, by employing CVaR and stress testing techniques, Ceres (2020) finds that more than half of major U.S. banks' syndicated loan portfolios are exposed to transition risks, since many banks have clients in sectors that are not aligned with the Paris Agreement.

CVaR assessments have also been applied to measure financial stability risk at the global level (see, for example, Dietz et al. [2016] and Carbon Disclosure Project [2019]). Morgan Stanley Capital International (MSCI) offers clients portfolio-level CVaR metrics, and the NYU Stern Volatility Laboratory created a risk estimation tool to quantify how climate change may affect the performance of financial assets.[7] Additionally, S&P Trucost's Carbon Earnings at Risk data set allows users to analyze company-level exposure to future carbon pricing policies based on current emissions.[8]

Limitations and discussion. CVaR analysis sheds light on how costly a range of outcomes, particularly tail-risk events, could be and provides baseline estimates of financial system damages. Continued research and data improvements could position CVaR as a helpful tool for analyzing CRFSRs.

However, since CVaR analysis is generally conducted at the portfolio level for individual institutions, it often captures only direct risks to portfolio valuations and cash flows without considering broader systemic effects. Moreover, these metrics quantify the extent of exposure, but translating results into meaningful actions and avoiding myopia may be challenging, since most climate-related risk is concentrated in the tail.

Natural capital analysis

In natural capital analysis, practitioners identify natural dependencies and risks to natural resources, and then examine their effects on operations and supply chains. Specifically, one can measure a firm's exposure to the degradation of natural resources (water stress, habitat destruction, and land erosion) by modeling natural resources (water, forests, and clean air) as a limited capital stock and assessing the future effects of its depletion. Rather than examining how institutions may damage natural resources, this methodology examines how environmental degradation may affect institutions' business models.

By definition, natural capital analysis is better suited to analyzing physical risks than transition risks, since it focuses on how the degradation of natural resources due to physical risks affects business activity. In the practitioners' space, the Natural Capital Finance Alliance (NCFA) partnered with UBS and Citi to launch the Exploring Natural Capital Opportunities, Risks, and Exposure (ENCORE) tool, designed to help banks better understand their natural capital dependencies and the potential impacts of natural capital degradation.[9] The NCFA also performed a natural capital analysis on five participating banks in Colombia, Peru, and South Africa (Natural Capital Finance Alliance and PricewaterhouseCoopers 2018).

Because natural capital analysis is less applicable to evaluating the effects of climate-related policies, technologies, and preferences, there are no such analyses examining the impacts of transition risk in the United States.

Limitations and discussion. Although concerns about biodiversity exist independent of climate change, natural capital analyses can be extended to measure CRFSRs given the linkages between climate change and changes in biodiversity. For instance, Calice, Kalan, and Miguel (2021) find that Brazilian banks are materially exposed to biodiversity loss through their domestic nonfinancial corporate loan portfolios and highlight this as a financial risk for the Banco Central do Brasil. For a comprehensive academic study on biodiversity risk and the ways in which economic activity and asset values are affected by physical and regulatory risks associated with biodiversity loss, see Giglio et al. (2023). Interest in the links between biodiversity loss and financial stability risks is growing, and the NGFS recently formed a group to research this topic further (Network for Greening the Financial System 2021).

2. Key Takeaways and Paths for Future Research

We now turn to discussing key takeaways from the existing research and avenues for future work.

2.1 Key Takeaways

A key message of this article is that we are closer to the beginning than to the end of integrating climate-related risks and financial system vulnerabilities into modeling frameworks. We find that most models in the existing literature focus on estimating the extent of economic harm and have yet to reach the stage where they are able to reliably assess risks to financial stability. In Table A1 in the appendix, we summarize the strengths, weaknesses, key assumptions, and applicability of each of the methodologies we review for modeling U.S. CRFSRs.

Future work on identifying, estimating, and developing policy around U.S. CRFSRs needs to overcome five key challenges particularly pertinent to climate risks: (1) handling uncertainty, (2) adapting methodology to handle long time horizons, (3) integrating heterogeneities across agents, assets, institutional structures, and portfolios, (4) allowing for technological changes, and (5) accounting for the indirect economic damages from climate change.

First, uncertainty in measuring CRFSRs may significantly undermine the validity of risk estimates. Uncertainty is present in both the sensitivity of climate risk to increased greenhouse gases in the atmosphere and in the reaction of agents (government, industry, and households) to a changing climate.[10] Most modeling approaches require strong assumptions about the future behavior of economic agents, future technological innovation and emissions pathways, the impact of emissions on climate, and the economic and financial consequences of climate change. Hence, a crucial effort must be made to evaluate the sensitivity of outcomes to these assumptions.

The high degree of uncertainty also implies that historical data need to be interpreted with caution, given that climate change negates the stationarity of key time series and makes estimated variances, covariances, and other statistical moments potentially unreliable. The majority of the most widely used methodologies in the literature suffer from this point. For example, many empirical studies using the statistical methods described in Section 1.1 produce estimates for the effects of climate shock on default rates, insurance premiums, or asset allocations based on backward-looking data, suggesting that one needs to exercise caution in extrapolating future impacts based on current models' historical estimates.

Second, future research needs to overcome the difficulty of addressing the long time horizon over which climate change might affect the financial system. Traditional methodologies usually forecast risks within a three- to five-year horizon, thereby ignoring changes in balance sheets, preferences, policy incentives, or other complicating factors in the longer term. However, going outside of this environment requires additional assumptions to model the evolution of dynamic balance sheets, physical systems, and discount factors. In particular, efficient pricing of long-lived financial assets requires consideration of a long time horizon in order to avoid potentially large price dislocations. For example, a thirty-year fixed-rate mortgage on a coastal property on the eastern seaboard should be priced according to a long-term forecast of the value of the underlying collateral, crucially including its climate-related risk. Determining where unmeasured climate risk may hide within the financial system requires this long-term view.

Third, future studies should address heterogeneities in financial markets and exposures of financial institutions. Specifically, these heterogeneities refer to the differential exposures of market participants, the widely spanning geographic locations of counterparties and collateral, the varying exposures across industries, and wide variation in institutional structures (for example, the U.S. regulatory landscape is divided across asset types and federal and state jurisdictions). This challenge extends beyond the traditional banking sector and includes heterogeneous exposures and responses in the insurance sector and other nonbank financial intermediaries, all of which complicates the modeling of climate-related risks.

While some general equilibrium models add richness in addressing heterogeneity, the standard assumptions used to make agents' behavior tractable, such as evaluating the effect of climate shocks on the financial system for a "representative firm," are ill-suited to fully reflecting heterogeneity. To the best of our knowledge, none of the current empirical studies that use a general equilibrium model with a financial sector embed multiple financial markets, instead writing a stylized model on one sector—for instance, the banking sector as in Diaz-Gimenez et al. (1992). Future models should be able to explain the various extents of climate exposures at different financial institutions that can be otherwise viewed as conflicting with an assumption of rational expectations. Moreover, incentives may differ so widely across a given class of agents that the representative agent assumption adopted by many methodologies is ill-advised.

Fourth, technological change may have two opposing effects. On the one hand, it is beneficial for mitigation and adaptation. On the other hand, it may cause legacy assets to experience devaluations and become stranded. Hence, understanding innovation is a crucial part of assessing CRFSRs, even though current methodologies either do not consider innovation or make simplistic assumptions. The magnitude of the technological and infrastructural changes of the last few decades should lead researchers to consider climate adaptation and mitigation through technological change as central ingredients in modeling CRFSRs.

Lastly, future research using, in particular, IAMs, as discussed above, will need to improve on damage functions, which map climate-related risks to economic and household welfare outcomes. These functions are important for determining the social costs of climate change and, in turn, the optimal policy responses. Damages, for example, include the negative effects on the labor market, capital stock, and natural capital. The tangible and nontangible effects of climate change are difficult to estimate, which may lead to poorly specified damage functions and noisy estimates of economic damages.

Table 1 summarizes the current potential of the methodologies discussed in Section 1 to address the five aforementioned challenges. The effort to address these challenges will benefit from development of new models and methodologies, more granular data, and novel techniques of imputation. The need for expanded data sets has already received much attention, particularly from financial authorities (see, for example, Financial Stability Board [2021] and Network for Greening the Financial System [2022]).

2.2 Paths for Future Research

The optimal strategy for future research on U.S. CRFSRs necessarily entails combining several methodologies, given that every methodology has different strengths and weaknesses,

Table 1
Potential Methodologies to Address Modeling Challenges in Quantifying U.S. CRFSRs

Methodology	Uncertainty	Long Time Horizon	Heterogene-ities	Technologi-cal Change	Damage Function
Statistical methods	Somewhat	No	Yes	No	No
General equilibrium models	Yes (DSGE)	Yes	Yes (CGE)	Yes (DSGE)	Yes
Integrated assessment models	No	Yes	No	Somewhat	Somewhat
Input-output models	Somewhat	No	Yes	No	Yes
Overlapping generations models	Somewhat	Yes	Yes	Somewhat	Yes
Agent-based models	Somewhat	Yes	Yes	Somewhat	Yes
Scenario analysis/stress testing/sensitivity analysis	Somewhat	Yes	Yes	Somewhat	Yes
Others	Somewhat	Somewhat	Somewhat	No	Somewhat

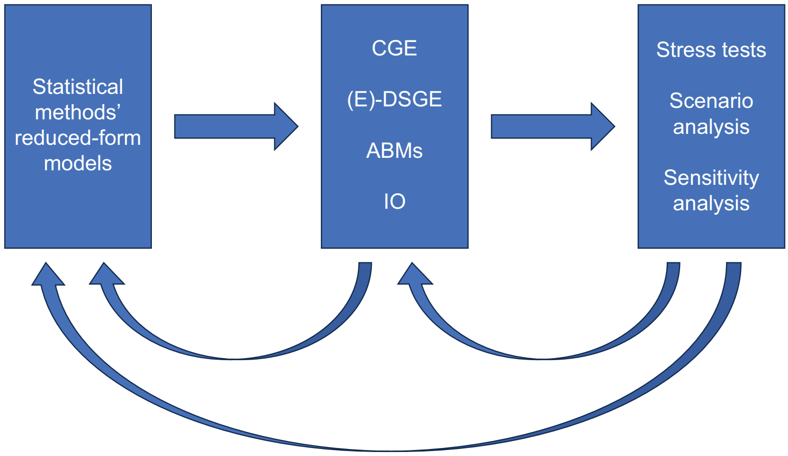
Note: This table summarizes the potential of the methodologies discussed in this article to address the challenges of handling uncertainty, adapting to handle long time horizons, integrating heterogeneities, allowing for technological change, and accounting for the indirect economic damages from climate change.

suitability and applicability, and level of potential to overcome modeling challenges. In particular, using a combination of agent-based models, general equilibrium models, input-output models, and statistical methods is an option that can help researchers obtain a more complete understanding of U.S. CRFSRs. Exhibit 2 illustrates this methodological chain and the complementary way that the different types of analysis can refine and improve the inputs and results of each of the preceding and succeeding methodologies. Outputs from statistical methods can be used to inform the main parameters and assumptions in CGEs, DSGEs, ABMs, and IOs as well as the distributions of different random variables in ABMs. The outputs can also be used to design scenarios that feed into stress testing, sensitivity analysis, and other approaches.

Similarly, outputs from CGEs and DSGEs can be used to inform pathways used in scenario analysis, stress testing, sensitivity analysis, and other approaches. For example, CGE models have proved useful in producing quantitative magnitudes of the regional, national, and sectoral economic impacts arising from extreme weather events. Hence, when researchers want to address physical risks, economic projections from CGE models could serve as valuable inputs for other analyses. Additionally, DSGE models allow for tracing the transmission channels between climate shocks and economic outcomes and, as a result, can produce useful inputs for other analyses addressing transition risk. Furthermore, IO models may help to evaluate the outcomes of complex CGE models while still incorporating heterogeneity and providing a simple tool for considering linkages among different sectors in the economy. Because these models rely on IO data, they do not require strict assumptions and they produce somewhat less uncertain outcomes.

Improvement in each of the individual methodologies to overcome current limitations will also be helpful for future research. In particular, most methodologies assume stationarity of

Exhibit 2
Methodological Chain to Study U.S. CRFSRs



Notes: This exhibit shows the methodological chain to study U.S. CRFSRs. Reduced-form outputs from micro- and macroeconometric statistical methods can inform the main parameters, fundamental assumptions, and probability distributions of key random variables in CGE models, DSGE models, ABMs, and IO models. This information could be useful for designing and conducting scenario analysis, sensitivity analysis, and stress tests. Methodologies are linked in a feedback loop whereby results along the methodology chain refine and improve the inputs and outputs of the other methodologies.

the underlying dynamic processes or the existence of well-behaved statistical moments. These assumptions may not be well-suited to analyzing the impact of climate change. The incompatibility between a traditional normal distribution of financial risks with known statistical moments and the skewed distribution of climate-related risks with uncertain statistical moments is not an easy problem to solve. Most of the behavioral frameworks for rational risk management assume the former, and the macro-empirical work on climate risks is difficult to interpret outside of the assumption of stationarity implied by a normal distribution of outcomes. ABMs offer the potential to relax these assumptions, and the computational power needed to implement ABMs is becoming increasingly within reach. While some models are beginning to apply more realistic assumptions and distributions, a large gulf exists between the promise and the current state of these models.

As computational power and solution techniques evolve, researchers will be able to build and solve more comprehensive dynamic equilibrium models. Significant advances in pseudo-agent-based modeling have been made for Europe (see, for example, the "stock-flow consistent" approach of Stolbova, Monasterolo, and Battiston [2018]), but not yet for the United States. As data quality and availability improve, statistical methods will be able to estimate new parameters and potentially unveil new correlations and heterogeneities.

Finally, for the United States, very little work has been done on the systemwide distribution of climate-related risks across counterparties, although the importance of the insurance sector for the banking sector's vulnerability to physical risks is well known. VaR models, scenario analysis, and stress testing represent a micro-level approach to complement the macro-level approach of the general equilibrium models. In general, the ability of a micro-level approach to address counterparty risk has yet to be realized, again because of a lack of disclosures and inadequate data. This leaves macroprudential climate analysis as a wide-open topic for interested researchers.

3. Conclusion

In this article, we reviewed ten broad classes of models that have been used to study financial stability risks arising from climate change. Surprisingly little is known about U.S. CRFSRs despite a significant expansion of the literature addressing climate risk over the last decade. We have identified several methodologies that are particularly promising for future research that have not yet been used to assess U.S. CRFSRs.

Anticipating the effects of climate-related risks requires accounting for fundamental uncertainty, complexity, and deviations from standard assumptions of financial risks. Moreover, the direct and indirect effects of the transition to a low-carbon economy are substantially different from the direct and indirect effects of physical risks. A potentially disorderly reallocation from a nongreen to a green economy might weaken the balance sheets of financial institutions, with potentially large economic and financial effects. Tracing these effects and assessing the likelihood of systemic failures are difficult tasks, and the challenge is compounded by a lack of granular and consistent data, agreement on asset classifications (for example, what it means to be a "green" or a "nongreen" asset), and poor cross-jurisdictional transparency.

Appendix: Data Requirements

We outline data requirements for each of the methodologies described in Section 1. It should be noted, however, that these assessments are incomplete, and a discussion of the full range of climate data gaps and challenges is outside the scope of this article. The NGFS Workstream "Bridging the Data Gaps"[11] provides more information on this topic, in addition to initiatives led by the Basel Committee on Banking Supervision and the Financial Stability Board.

Statistical Methods

Statistical methods require detailed and granular data. In particular, analysis of the effects of extreme climate events on financial institutions requires (1) loan-level data at a monthly or quarterly frequency for various asset classes, such as corporate credit to firms and commercial and residential mortgages, among others, and (2) data on security-level holdings. These data sets are commercially available for a subset of nonbank financial institutions and are collected, for banks only, by the Federal Reserve to assess banks' capital adequacy and to support stress testing. However, the Federal Reserve collects these data only for very large banks. Hence, a considerable data gap exists for smaller banks and other types of financial institutions, such as insurance companies, pension funds, and investment managers.

Computable General Equilibrium Models

Data needed for CGE model calibration include social accounting matrices (SAMs), which are derived from National Income and Product Accounts (NIPA); input-output tables; quantities and prices of inputs such as labor, capital, and energy sources; and financial variables. Data gaps exist in calibrating key supply and demand parameters, including the elasticity of substitution and production cost functions, often resulting in an ad hoc selection of values based on best judgment. This may lead to uncertainty in the accuracy of the new equilibrium under the perturbation of climate-related parameters.

Dynamic Stochastic General Equilibrium Models

Studies using DSGE models both calibrate—using commonly adopted values in the literature, surveys, or meta-studies—and estimate structural parameters using historical data. Data requirements are similar to those of CGE models, and as with CGE models, data gaps are particularly severe in determining certain parameters, including substitutability and discount rates. Thus, results may be sensitive to assumptions for these parameters.

Integrated Assessment Models

Detailed climate and economic data are required to construct the interlinked modules that compose IAMs. Climate data often need to include projections for geophysical factors, such as global mean temperatures and solar radiation, as well as possible pathways for greenhouse gas emissions, energy and land use, technological advancements, and social and governance changes. These are in addition to the economic data needed for large-scale, economy-wide cost-benefit and cost-effectiveness analyses, such as the projected pathways of macroeconomic indicators.

Appendix (Continued)

Input-Output Models

The application of IO models to assess U.S. CRFSRs requires at least three sets of industry-level data: (1) the domestic supply and use of commodities, (2) environmental data on resource use, and (3) financial data, such as U.S. banks' and nonbank financial institutions' exposures by industry. Additionally, since climate-related risks can affect U.S. financial institutions through both domestic and foreign exposures, linkages with foreign industries might need to be considered.

Overlapping Generations Models

Overlapping generations models are primarily theoretical and do not require much data.

Agent-Based Models

These models require detailed data to develop agents' behavioral rules and program networks to capture agent-interaction effects, reflecting the computationally intensive nature of this methodology. Information about agents (firms, households, businesses, the government, etc.), their relationships to each other, and the environment in which they operate is required. It is up to the modeler to determine how granular these data on agents and their environment should be, but the level of specification of input data will determine the level of detail of output data.

Scenario Analysis, Stress Testing, and Sensitivity Analysis

Since these methods are often applied at the asset and portfolio level and require that level of granularity for an institution- or system-level assessment, they require detailed climate, economic, and financial data. Data requirements can include geolocations of assets and operations at a granular level, since the same region may face different levels of risks (for example, if the area has vulnerable coastal locations near less exposed mountainous regions). Additional data requirements include credit ratings; asset valuations; portfolio exposures; firms' Scope 1, 2, and 3 emissions; supply chain pathways and dependencies; and projected climate and macroeconomic pathways. More broadly, consistent climate data disclosures from financial institutions would be necessary for conducting standardized risk assessments at a system level.

Climate Value-at-Risk

This methodology requires detailed firm-level balance-sheet data to measure what percentage of a portfolio may be devalued owing to climate-related risks under different scenarios. These scenarios apply detailed data on projected climate pathways to simulate financial impacts under different climate outcomes. For a system-level analysis, individual institutions' balance-sheet data can be aggregated to shed light on the magnitude of U.S. CRFSRs.

Natural Capital Analysis

Instead of requiring firm-level balance-sheet and operational data to measure institutional effects with respect to nature and climate, this type of risk assessment requires data on a firm's natural capital dependencies to assess balance-sheet and operational impacts. Thus, researchers will need to identify an institution's natural capital dependencies and use data on projected

Appendix (Continued)

climate pathways to identify when and to what extent physical risks may degrade those dependencies. Finally, they will need to integrate this information with data on institutions' operations, supply chain pathways, and balance sheets to assess the impacts of natural capital degradation on firms' financial and operational health.

Others: Climate Risk Scores and Ratings

These metrics are primarily created by private data providers that do not disclose their methodologies. Without source methodologies, it is difficult to pinpoint the exact data used to develop these scores and ratings. Nonetheless, since these metrics are generally conducted at the asset, portfolio, and institution level to assess climate-related risks, they are likely to require granular balance-sheet data, geolocations of assets and operations, and information on firms' Scope 1, 2, and 3 emissions, in combination with data describing future climate and economic pathways, often derived from scenarios.

Table A1

A Comparison of Methodologies in Climate-Related Economic Studies

Methodology	Strengths	Weaknesses	Time Horizon vs. Complexity	Applicability	Key Assumptions	Modeling U.S. CRFSRs
Statistical methods	Intuitive and relatively easy to estimate and interpret	Rely on partial equilibrium view of the world; mostly focused on past data	Short to long term	Highly applicable	Tend to ignore equilibrium considerations	Can be combined with other methodologies
Computable general equilibrium (CGE) models	Quantify general equilibrium effects by accounting for interlinkages across many economic sectors and agents; can be flexibly adjusted to multisector, multicountry global setups	Strong assumptions, including perfect information; a "black box" approach	Short to long term	Somewhat applicable	Perfect information, exogenous technology, no adjustment costs in production, and inelastic supply of labor	Economic outcomes from the model can be fed into a macro-financial analysis to assess CRFSRs
Integrated assessment models (IAM)	Integrate climate and economic projections; projections are internally consistent; allow for cost-benefit analysis of climate mitigation	Most IAMs do not model money, finance, or banking; highly aggregated; typically rely on a smooth scalar damage function of chronic physical risk; lack resiliency to imperfect information and unforeseen endogenous events such as technological or policy changes	Short to long term	Highly applicable	Highly aggregated, general equilibrium theory, simplified climate models	Useful for generating scenarios for other methodologies
Overlapping generations models	Highlight intergenerational redistribution; incorporate life-cycle investment decisions	Closed economy models; do not consider endogenous systemic risks (climate change or transition)	Long term	Complex; marginally applicable	Usually assume perfect foresight about future prices	Could be useful for studying asset price implications and policy conflicts across generations

(Continued on next page)

Table A1: (*Continued*)

Input-output models	Detail environmental impacts at industry level; can capture impacts of demand for goods and services on energy and resources; computationally simple and require fewer assumptions	Cannot capture big technological advances as they are based on historical input-output tables; mainly focus on supply chain disruptions; require industry-level environmental and linkages data	Short to medium term	Marginally applicable	Assume that history is representative of future trends	Account for network effects; can be combined with other methodologies
Agent-based models	Capture interactions and feedback mechanisms between agents and the financial and real economy; Incorporate heterogeneous agent assumptions; accommodate network effects	Require detailed data to build agents' behavioral rules; agents' behavior may not be rational and representative	Short to long term	Complex	Rational expectations and perfect information	Account for network effects and risk amplification mechanisms
Scenario analysis, stress testing, sensitivity analysis	Examine multiple future pathways and outcomes; helpful for risk management and strategic decision- making; applicable to many stakeholders; do not require extensive modeling capacity	Limited climate and financial data available	Short to long term	Highly applicable	Detailed financial and climate data	Forward-looking nature helpful for risk management and quantification
Other approaches	Simpler than traditional modeling methods; applicable to many stakeholders	Scores and ratings have different methodologies, making comparison and interpretation difficult; most risk from climate VaR analyses is concentrated in the tail; may inadvertently enable myopia	Short to long term	Highly applicable	Detailed financial and climate data	Climate VaR helpful for quantifying extent of systemic exposure; natural capital analysis is somewhat applicable for risk management

Notes

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[1] For data on disasters, see National Oceanic and Atmospheric Administration, National Centers for Environmental Information (2022), "Billion-Dollar Weather and Climate Disasters: Events," at https://www.ncei.noaa.gov/access/billions/events/US/2021?disasters[]=all-disasters. For wildfires in California, see "2021 Fire Season Incident Archive," at https://www.fire.ca.gov/incidents/2021/.

[2] Several CGE models are widely used for climate analysis in the United States, including the environment-energy-economy model (E-3 model), MIT's emissions prediction and policy analysis (EPPA) model, the G-cubed model, the Global Trade Analysis Project (GTAP) model, and the intertemporal general equilibrium model (IGEM). See Chen et al. (2015), Corong et al. (2017), Chen, Goulder, and Hafstead (2018), Jorgenson et al. (2008), and McKibbin and Wilcoxen (1999).

[3] A subset of IAMs called policy optimization models (POMs) include a third module for the economic damages of climate change (Intergovernmental Panel on Climate Change 2001). In this module, the damage function calculates economic damages based on inputs from the economic and climate modules.

[4] Scenario analysis, stress testing, and sensitivity analysis can be applied to estimate vulnerability to both chronic and acute physical risk. For chronic risks, these methodologies will typically use a scenario projecting incremental changes in long-term climate patterns such as temperature, precipitation, or sea level, and model how an incrementally harsher climate could lead to a buildup of vulnerabilities. For acute physical risks, these methodologies are used to estimate the impact of extreme events on firms' operations and financial health.

[5] See the NGFS Scenarios Portal, https://www.ngfs.net/ngfs-scenarios-portal/use/.

[6] Information on how Scope 1, 2, and 3 emissions are defined can be found at https://www.epa.gov/greeningepa/greenhouse-gases-epa.

[7] For more information, see MSCI's product website, https://www.msci.com/our-solutions/esg-investing/climate-solutions/climate-data-metrics, and the NYU Stern Volatility and Risk Institute's climate website, https://vlab.stern.nyu.edu/welcome/climate, respectively.

[8] For more information, see S&P's product website, https://www.marketplace.spglobal.com/en/datasets/trucost-carbon-earnings-at-risk-(184).

[9] See https://encore.naturalcapital.finance/en.

[10] The physical climate system is a complex structure with five major components: the atmosphere, the oceans, the cryosphere (snow and ice), the land surface, and the biosphere. In addition, the direct and indirect effects of climate change on economic outcomes—ranging from crop yields to the productivity of outdoor workers—and the effects on financial variables and policy responses are only just beginning to be studied.

[11] See Network for Greening the Financial System (2022). Additional information can be found at https://www.ngfs.net/en/about-us/governance/workstream-bridging-data-gaps.

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