An input–output sensitivity analysis of climate–economy integrated assessment models

Quantifying underlying model assumptions and differences in climate scenario projections based on social and economic variables

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Abstract

This paper analyses the underlying interactions between input and output variables of three process–based climate–economy integrated assessment models according to a standardised subset of social and economic input variables, and how they contribute to variability in scenario outputs. This paper compares two key climate scenario output variables of transition risk, including carbon sequestration and technology costs, modelled according to the three IAMs used by the Network for Greening the Financial System: GCAM, REMIND–MAgPIE, and MESSAGEix–GLOBIOM. Evidence shows variability in the outputs of NGFS under the same policy ambition, the same temperature target, and the same social and economic input data. Using a cumulative distribution sensitivity analysis (PAWN) to compare IAM input data to output trends, this paper observes the sensitivity of model input variables to driving differences in scenario outputs according to underlying interactions and assumptions between social and economic variables. Findings demonstrate that differences in climate scenario trajectories under the same narrative pathways can be distinguished according to sensitivities of a standard subset of input variables from the SSPs. Understanding the sensitivity of climate scenario trajectories to a standard set of social and economic input variables can help financial institutions in the selection, categorisation, and application of different IAMs, scenarios, and pathways for financial analysis.

Acknowledgments

This research was supported through the UK Centre for Greening Finance and Investment. We would like to thank Gireesh Shrimali for his valuable guidance, Christopher Cormack, Scott Aguais, and Abhinav Jindal for their useful comments and suggestions. The views expressed in this paper are those of the authors only and do not necessarily reflect those of the University of Oxford or the University of Bristol.

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1 Introduction

Financial institutions, including banks, investors, asset managers or insurers, attribute an increasing importance to and risk from climate change due to financial exposure coming from volatility and uncertainty in the real economy, environmental and transition policy, physical climate risk, and social changes.[1] In order to address the uncertainty surrounding these issues, financial institutions have begun exploring climate scenarios to better understand and identify the potential issues they face. Climate risks represent significant challenges for finance that can directly translate to real values, financial behaviours, planning, and strategy. Understanding these risks and mitigating against these uncertainties are vitally important to develop and manage decarbonisation strategies for the future. In order to develop decarbonisation strategies and climate risk plans, financial institutions need a sense of the potential trends or patterns that are associated with these risks. These unknown trends include questions on the cost and deployment of renewable technologies, and the rate, stringency, and coverage of environmental policies.

In order to gain a better sense for the potential trends and trajectories, financial institutions have begun exploring climate scenarios, where several of these variables are incorporated into forecasting models, such as those produced by process–based climate–economy integrated assessment models (IAMs). These models forecast potential trends and pathways of the global economy to reach certain climate goals under various climate, economic, and political conditions. However, while these models and their trajectories have become widely adopted by financial institutions for assessing risk, they provide a wide and variable range of output trends of the future. The range of forecast trends under different modelling techniques and assumptions, but under the same temperature target or policy ambition can lead to extensive uncertainty in the selection, confidence, and applicability of climate scenarios for practitioners, with significant implications for financial institutions.[2]

The uncertainty underlying both the modelling and their pathways has been widely cited, "the emissions price that internalises the resulting damages depends on uncertain future growth in productivity and consumption, on uncertain future greenhouse gas emissions, on the uncertain degree to which emissions will generate warming, and on the uncertain channels through which warming will impact consumption and the environment. However, the primary tools for assessing physical and economic climate related risks have been based on deterministic climate–economy

[1] Stefano Giglio, Bryan Kelly, and Johannes Stroebel. "Climate Finance". In: *Annual Review of Financial Economics* 13 (2021), pp. 15–36.

[2] Luke J. Harrington, Carl-Friedrich Schleussner, and Friederike E.L. Otto. "Quantifying uncertainty in aggregated climate change risk assessments". In: *Nature Communications* (2021).

models that ignore uncertainty, and recent recursive dynamic programming versions of these models often do not provide theoretical insights."[3]

In a study that looked at consistent climate stress tests applied to a set of three different net zero 2050 target scenarios, Gasparini, Baer, and Ives (2023) show that the variance in the pathway to the net zero 2050 target based on differences in scenarios can lead to significant variance in the projected valuation of companies.[4] This can subsequently contribute to variability in the assessment of portfolio–level VaR, and institutional investor's climate resilience. Hence, the selection and application of climate scenarios and pathways is central to evaluating their physical and transition risk. However, the way in which the output trajectories of climate scenarios are developed is highly complex, and the key assumptions upon which such trajectories are based are not well–understood.[5] Yet there are several climate scenarios producing a wide range of output projections, making the reliability and selection of one scenario over another difficult to assess, categorise, and inform financial institutions.[6] Building on the findings of Gasparini et al. (2023) showing how different climate scenario trajectories can lead to widely different impacts on company valuation and portfolio VaR, this paper looks at what is driving variability in climate scenario outputs based on the model inputs and how they influence different trajectories under the same policy ambition and temperature target.

Due to the variety of pathways provided by climate scenarios for the same narratives, there is extensive uncertainty in the use and application of climate scenarios by stakeholders and practitioners, who are in the early stages of implementing climate scenarios in financial analysis. Given the uncertainty, practitioners need to consider several different scenario trajectories. However, given the complexity of the scenarios, there is not an easy or efficient methodology or categorisation upon which practitioners would be able to select or differentiate one scenario over another.[7]

Given the lack of a common methodology or taxonomy for identifying and selecting between different climate scenarios, the tendency is to say that differences between scenario data signify differences between outcomes that are likely to materialise in reality, without fully considering the underlying assumptions in how the scenario was derived. This can lead to both a lack of implementation and application of climate scenarios for financial analysis. However, even if practitioners

[3] Derek Lemoine. "The climate risk premium: How uncertainty affects the social cost of carbon". In: *The Association of Environmental and Resource Economists* 8.1 (Jan. 2021), pp. 27–57.

[4] Matteo Gasparini, Moritz Baer, and Matthew C. Ives. "A re-evaluation of the financial risks of the net zero transition". In: *Oxford Working Paper* (2023), pp. 1–39.

[5] Andreas F. Prein et al. "A review on regional convection-permitting climate modeling: Demonstrations, prospects, and challenges". In: *Reviews of geophysics* 53.2 (June 2015), pp. 323–361.

[6] Geoffrey Heal and Antony Millner. "Uncertainty and decision in climate change economics". In: *National Bureau of Economic Research Working Paper Series* 18929 (Mar. 2013), pp. 1–26.

[7] Lars Peter Hansen and William Brock. "Wrestling with uncertainty in climate economic models". In: *Becker Friedman Institute for Economics Working Papers* 71.1 - 69 (2018).

had correctly specified models, additional conditions are needed to sustain inferences about differences between scenario pathways. The calculation of uncertainty raises difficult issues, especially when the underlying in–sample distributions are identical for several 'potential' outcomes when the pathways are set as deterministic functions, such as setting the specific temperature target or policy ambition. Under these circumstances, a scenario comparison adds little beyond testing for the significance of the perturbed variable in the estimated model, such as the global temperature target or the carbon tax. However, when models include multiple covariates, inferences about scenario differences depends on the relationships between the conditioning variables, especially their invariance to the interventions being implemented.

Therefore, while climate scenario models are highly complex and involve multiple covariates, understanding how these variables relate to the conditioning variables provides a measure of comparison of the underlying modelling that is driving differences in scenario outputs under the same policy ambition. Understanding and categorising these differences can subsequently help better understand how differences in trends and trajectories result from the same temperature target, and the same underlying distributions.[8] Therefore, this paper looks at what drives the differences in climate scenario outputs when identical inputs are used as exogenous variables against which climate scenario projections have been conditioned.

Standardised exogenous input variables have been widely adopted across climate scenarios, which are based on key social and economic assumptions of the future.[9] Since these key social and economic assumptions are broadly and consistently applied across IAMs, understanding how they are modelled within each scenario helps practitioners identify differences between them. Understanding how the underlying social and economic assumptions influence scenario outputs can help practitioners and financial institutions better differentiate between the wide range of scenario trajectories, which can, as shown by Gasparini et al. (2023), significantly affect company valuations and portfolio VaR. Key climate scenario outputs, such as the availability and amount of carbon sequestration technologies, or the cost and deployment of renewable technologies, are calibrated against key social and economic variables, such as economic and population growth, or sectoral price elasticities. While these assumptions are broadly consistent across IAMs, differences in scenario outputs are premised on differences in how each of these social and economic factors drive output trends from IAMs.

[8] Harrison Hong, G. Andrew Karolyi, and Jose A. Scheinkman. "Climate Finance". In: *The Review of Financial Studies* 33.3 (2020), pp. 1011–1023.

[9] Thomas Allen et al. *NGFS Climate Scenarios for Central Banks and Supervisors*. Tech. rep. Network for Greening the Financial System Macrofinancial Workstream, June 2021.

For example, several studies have highlighted that progress towards decarbonisation in the economy and the energy system is unlikely to be met under existing conditions, and instead requires rapid and drastic change that is either enforced by government policy, or induced by social and economic change.[10] These studies have highlighted how complex and adaptive systems can undergo rapid change according to critical social and economic thresholds or tipping points, such that a relatively small change can trigger a larger one that becomes irreversible, where nonlinear feedback effects act as amplifiers.[11] Recent studies have identified these critical thresholds as sensitive intervention points where rapid change can occur from social and movements that galvanise action, investment, and policy in a way that drives a larger system change, such as the deployment of renewables in the energy system.[12] Similarly, modest, but highly targeted government policies can have amplifying effects on broader mitigation efforts across economic sectors.[13] These types of nonlinear feedback effects are not directly incorporated in climate economy models, but are key assumptions of social and economic change that are included as model inputs. For IAMs, several societal assumptions that are made based on the evolution of society, the global economy, and consumer preference that are not able to account for the potential for critical social thresholds.[14]

While the potential for social and economic factors to shift decarbonisation trajectories is often understood qualitatively, trends of social and economic change are incorporated quantitatively as general assumptions of IAMs, and are selected on the basis of consensus in the academic community.[15] These assumptions on broad social and economic change enter IAMs as exogenous variables, against which other variables are calibrated and projections on key climate scenario output variables are derived. As such, the quantitative basis of social and economic variables in IAM model inputs can be similarly quantitatively analysed to distinguish between climate scenario outputs, when forecast trajectories differ under the same social and economic assumptions, and the same temperature target.

In order to identify how exogenous social and economic input variable assumptions influence the variability in key output variables for climate scenarios, and to identify the potential for critical thresholds and tipping points that drive differences in narrative pathways, this paper employs a method of global sensitivity analysis of a common set of input variables used across climate

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[10] Rupert Way et al. "Empirically grounded technology forecasts and the energy transition". In: *Joule* 6.9 (2022), pp. 2057–2082.

[11] Derek Lemoine and Christian P Traeger. "Tipping points and ambiguity in the economics of climate change". In: *National Bureau of Economic Research Working Paper Series* 18230 (2012).

[12] J. Doyne Farmer et al. "Sensitive intervention points in the post-carbon transition". In: *Science* 364.6436 (Apr. 2019), pp. 132–134.

[13] Marshall Burke and Kyle Emerick. "Adaptation to climate change: Evidence from US agriculture". In: *American Economic Journal: Economic Policy* 8.3 (2016), pp. 106–140.

[14] Allen et al., *NGFS Climate Scenarios for Central Banks and Supervisors*, op. cit.

[15] Christoph Bertram et al. *NGFS Climate Scenarios Database*. Technical Documentation. Network for Greening the Financial System Macrofinancial Workstream, June 2020.

scenarios compared to key scenario output variables of interest for financial risk provided by the Network for Greening the Financial System (NGFS). In section 2 the paper discusses the set of output variables used in this study as the key transition risk variables provided by the NGFS. In section 3 the key social and economic input variables from the shared social–economic pathways (SSPs) that are inputs to the NGFS climate scenarios are discussed. Section 4 explains the PAWN method of sensitivity analysis. Section 5 shows the results of the analysis of projections on the amount of carbon sequestration under the three IAMs. Section 6 assesses the results of the sensitivity analysis on projections of the capital costs of wind. Section 7 concludes.

2 Data: Output Variables

Climate and economy scenario projections of future trends and pathways to 2100 generated from process-based IAMs have been used by financial researchers, investors, and institutions to inform financial analysis and decision making. The IAMs and scenarios that have become widely used by financial institutions are those that have been composed by the Network for Greening Financial Stability (NGFS). The NGFS scenarios are intended to provide financial institutions and authorities a common set of scenarios for the purpose of climate financial risk assessment, thereby promoting harmonisation in the scenario assumptions, and increasing comparability of scenario analysis results and disclosures.[16] The scenarios designed by the NGFS to support financial institutions and financial decision making are based on predictions or possible narrative pathways of how the countries will transition to a more sustainable future economy. Given the uncertainty of any future prediction or trajectory, the NGFS has developed three broad categories of transition pathways: an orderly transition, a disorderly transition, and no further policy changes or action. For each of these three categories, they have developed a high and low variant of the future trajectory to 2050 and 2100. Thus, there are a total of six different future projection pathways.

The six different pathways are characterised by their differences in the level of physical and transition risk. Differences in the level of transition and physical risk under each of the six pathways drives the differences in the trend projections to 2050 and 2100. Monasterolo et al. (2023) has characterised the risk channels that drive the differences under each of the six pathways. They have identified five risk channel types that drive projections around physical and transition risk. The level of policy ambition is the physical risk channel. Policy reaction, technology change, carbon sequestration, and regional carbon price variation are transition risk channels. The relationship between how each risk channel drives the differences in trends under each of the six narrative

[16] Ibid.

pathways for the NGFS is summarised in table 1 by Monasterolo et al. (2023).[17]

		Physical risk	Transition risk			
Category	**Scenario**	**Policy ambition**	**Policy reaction**	**Technology change**	**Carbon sequestration***	**Regional carbon price variation**
Orderly	Net Zero 2050	1.5°C	Immediate	Fast	Medium	Low
	Well-below 2°C	1.8°C	Immediate	Moderate	Medium	Low
Disorderly	Divergent Net Zero Policies	1.5°C	Immediate	Fast	Low/Medium	Medium
	Delayed 2°C	1.7°C	Delayed	Slow/ Fast	Low	High
Hot House World	Nationally Determined Contributions (NDCs)	2.5°C	NDCs	Slow	Low	Limited
	Current Policies	3°C+	Current policies	Slow	Low	Limited

Macro-financial risk level: Low, Medium, High

Fig. 1: Representation of the risk drivers in the NGFS scenarios. NGFS (2021a)

Some of these risk channels are almost directly represented as output variables from the NGFS scenarios, including "carbon sequestration", which is observed according to the amount of carbon that is removed from each sector to 2100, and "technology change" which is represented in the scenario output variables by the energy cost of different technologies over the century. Additionally, "regional carbon price variation" is observed from the outputs of the scenario pathways according to the energy supply and the energy price by sector and by geographic region. Trends for how these three transition risk drivers is observed in the proxy output variables according to each of the six narrative pathways is shown in figure 2.

In addition to the six narrative pathways developed on different assumptions of the level of physical and transition risk through the five risk drivers, the NGFS has modelled each of the narrative pathways in three different IAMs. The six different narrative pathways projecting how the transition to sustainability over the century will unfold are generated according to three different IAMs that are modelled and vetted by the IPCC: GCAM, MESSAGEix-GLOBIOM, and REMIND-MAgPIE. The selection of a set of IAMs used by the NGFS, rather than choosing one or another is in part due to the fact that there are differences in how the five risk drivers are modelled according to the three IAMs. The three IAMs each model the interactions between the climate and the economy differently, thus for each of the six narrative pathways that lay out a future of the global economy, there are three different trends modelled under each of the three IAMs used

[17] Irene Monasterolo, Maria J. Nieto, and Edo Schets. "The good, the bad, and the hot house world: Conceptual underpinnings of the NGFS scenarios and suggestions for improvement". In: *Documentos Ocasionales* 2302 (2023), pp. 1–30.

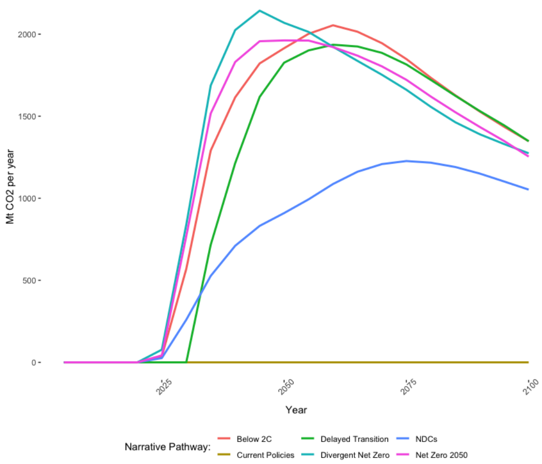
by the NGFS. Thus, in total there are eighteen different trends modelled across six pathways and three different IAMs.

The variety of future trajectories allows financial institutions to compare trends, outcomes, and provides added information and insights into the uncertainty around long-term projections of the global economy. While the NGFS scenarios provide significant information to assist with financial decision making by providing a wide set of six future pathways, each modelled under different techniques between three different IAMs, the uncertainty in how the five risk channels subsequently correspond to the output variables that represent physical and transition risk to inform financial decision making is less well known or understood. This can have significant implications for financial institutions, since the selection of either one or more pathways using one or more of the IAMs can lead to a wide range of scenario projections of physical and transition risk. This can have significant implications for financial institutions when calculating transition risk. As previously discussed, the choice in the transition pathway under the same policy ambition or temperature target can lead to wide variation in the assessment of corporate valuation.[18] This can have significant implications for the assessment of risk and the decision making of the companies themselves, and the financial institutions financing those companies. Therefore, it is key that financial institutions can accurately select the most appropriate set of scenarios and transition pathways to inform their decision making by understanding how the some of the key output variables that represent transition risk are modelled based on the assumptions or relationships between key input variables.

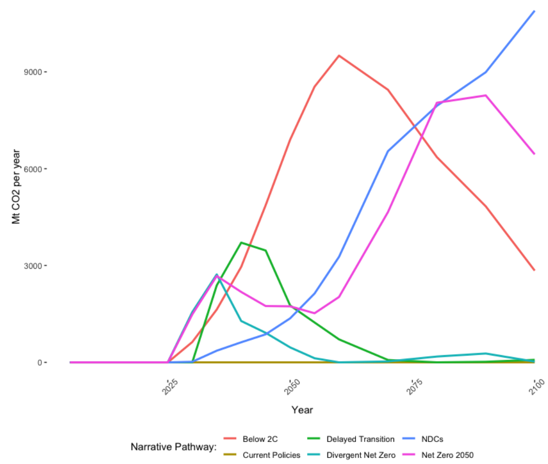
3 Data: Input Variables

In process-based IAMs such as the three being used by the NGFS, including GCAM, MESSAGEix-GLOBIOM, and REMIND-MAgPIE, the uncertainty in the projections of physical and transition risk emerges from the set of databases that standardise climate and social economic outcomes independently of the interactions between the two. The IAMs draw from two distinct databases representing climate and socio-economic projections, each of which drives the uncertainty in the risk channels for physical and transition risk. For physical risk, the uncertainty comes through the level of climate change, which is projected through the representative concentration pathways (RCPs). For transition risk, the uncertainty in risk channels of carbon sequestration, technology change, and regional carbon price variation are based on a set of social and economic projections on

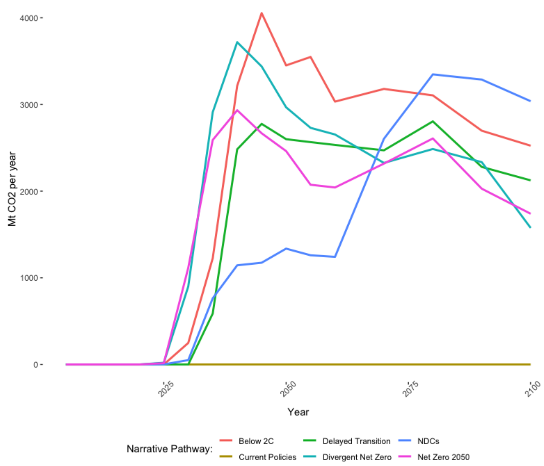
[18] Gasparini, Baer, and Ives, "A re-evaluation of the financial risks of the net zero transition", op. cit.



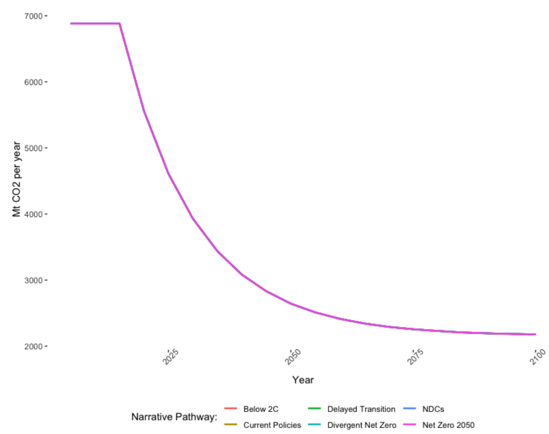
(a) GCAM: Carbon Sequestration: Fossil Fuels: Narrative Pathways



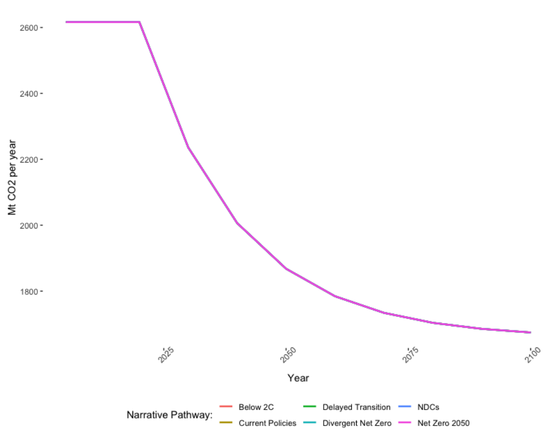
(b) MESSAGEix: Carbon Sequestration: Fossil Fuels: Narrative Pathways



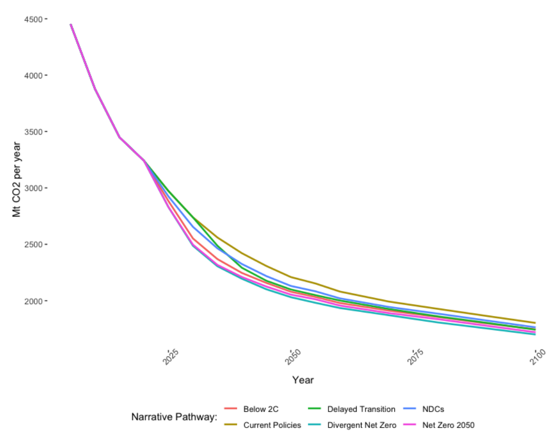
(c) REMIND: Carbon Sequestration: Fossil Fuels: Narrative Pathways



(d) GCAM: Capital Costs: Solar: Narrative Pathways



(e) MESSAGE: Capital Costs: Solar: Narrative Pathways



(f) REMIND: Capital Costs: Solar: Narrative Pathways

Fig. 2: Difference in narrative pathway trends by IAM

assumptions of future social and economic developments built through the datasets of the shared socio-economic pathways (SSP).[19]

SSPs and RCPs are central in the scenario literature informing the assessment reports of the IPCC, as both of datasets jointly define the framework within which IAMs develop climate scenario projections of physical and transition risk. Hence, understanding how SSP or RCP data are relatively modelled within the IAM sheds light on how best to interpret or understand the uncertainty in the estimation of risk from the IAM's key transition or physical risk outputs. For example, SSP data includes variables such as country-level GDP and population. These variables are then treated as inputs to an IAM, which can then have a considerable bearing on output variables that are relevant for transition risk. For example, projections of country-level GDP and population projections from the SSPs can significantly influence the IAM outputs on energy demand, or the country's ability to absorb adverse shocks or changes to the policy environment. Consequently, outputs of the IAM such as energy demand can significantly affect a country's response to policy changes in carbon prices, and the cost of technology, variables that are key for financial institutions to assess their transition risk. As IAMs produce a range of outputs that are important for financial institutions to determine their level of transition risk, it is important to understand how the uncertainty in key transition risk variables are influenced or driven by the key assumptions in the IAM model environment.

SSPs consist of a range of narrative pathways articulating trends on how societies and national economies will evolve over the century. They are broad assumptions of the future, but they are central to contextualising the setting in which the climate scenario occurs. For example, narratives such as a world in which consumption patterns become more sustainable would have a market reduction in forecasted emissions, whereas a world in which fossil–fuel development continues will either increase emissions or reinforce current pathways. Hence the choice in a set of SSP data determines the key assumptions that are driven and propagated in the resulting scenario forecasts. Nevertheless, such assumptions need to be made, and are generally standardised across IAMs to coordinate climate scenario modelling. The generally standardised variables that are most widely applied are projections of population, GDP, and rates urbanisation. Other variables of social and economic change that potentially influence the projection of key transition risk variables are variables such as labour productivity, elasticity of energy demand and land use changes from various sectors including industry, agriculture, transportation, etc. Additional variables provide detailed narratives describing the process of technological advancement, international cooperation, and

[19] Monasterolo, Nieto, and Schets, "The good, the bad, and the hot house world: Conceptual underpinnings of the NGFS scenarios and suggestions for improvement", op. cit.

resource use for a wide range of countries and regions up to 2100.[20] Hence, understanding how these variables relate to the uncertainty around key channels of transition risk helps FIs and other stakeholders in selecting the correct IAMs and narrative pathways, when risk assessment and company valuation can produce a range of results depending on the selection of IAMs and scenarios.

The SSPs define the prevailing socioeconomic challenges to adaptation and mitigation given a specific climate change outcome.[21] However, they have several limitations. First, they were last updated in 2017, and consequently do not account for changes that would have happened since then. Second, SSPs do not account for the role of finance, including monetary and fiscal decisions, even though these could be significant factors influencing climate mitigation and adaptation. For example, challenges to mitigation and adaptation will be lower if firms, especially those in low-income regions and countries, have better access to capital. Despite some of the shortcomings of the SSPs, they are applied to the IAMs as exogenous inputs that drive the variability in scenario pathways, and the range of outputs in transition risk. Therefore, understanding how the SSPs interact with, and how they are represented in the IAMs is key for financial institutions in selecting the key IAM output variables for determining their level of transition risk.

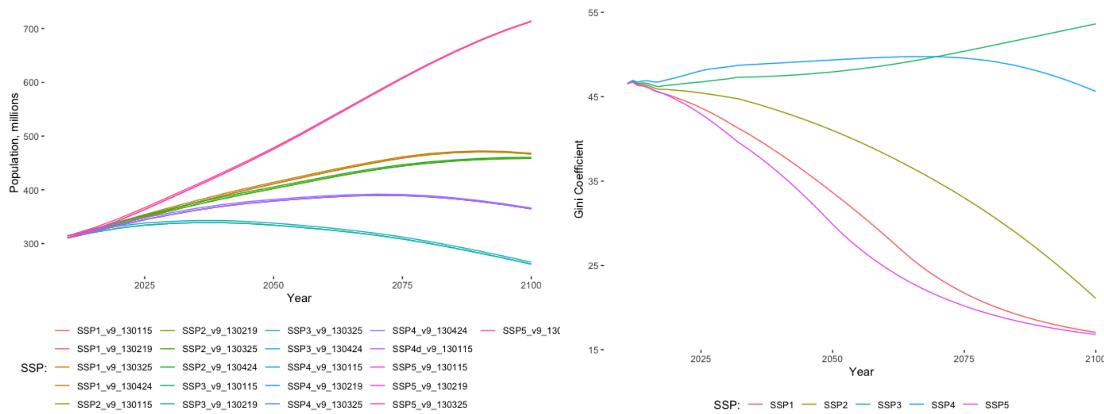
The SSP datasets include five different scenarios for how the global economy will develop over the century. The five scenarios range according to different narrative pathways about globally coordinated efforts towards mitigation and adaptation. They range from the most ambitious efforts, or a narrative pathway of sustainable development, followed by a middle of the road development, regional rivalry, inequality, or continued fossil fuel development. Figure 3 shows the difference in the population trends to 2100 based on the five different SSP scenarios. Pederson et al. (2021) have compared long-term historical developments of key social-economic drivers in relation to GHG emissions from 1990 to 2018 to determine if SSPs are still plausible, considering the latest insights. The authors conclude that global emissions generally follow a medium-high pathway, captured by the "middle of the road" SSP scenario.[22] This corresponds to the SSP narrative chosen by NGFS, using SSP–2.

The SSP–2 narrative pathways include a large set of data projections that characterise several variables of the global economy. These social and economic variables from the SSP–2 scenario are then taken as inputs into the IAMs used by the NGFS as baselines for the six NGFS scenarios. Additionally, in order to be consistent across IAMs, the same SSP–2 input data that describes social

[20]Keywan Riahi et al. "The shared socioeconomic pathways and their energy, land use, and greenhouse gas emissions implications: An overview". In: *Global Environmental Change* 42 (Jan. 2017), pp. 153–168.

[21]Elmar Kriegler et al. "The need for and use of socio-economic scenarios for climate change analysis: A new approach based on shared socio-economic pathways". In: *Global Environmental Change* 22.4 (2012), pp. 807–822; Brian C. O'Neill et al. "New scenario framework for climate change research: The concept of shared socioeconomic pathways". In: *Climatic Change* 122.3 (2014), pp. 387–400.

[22]Jiesper Strandsbjerg Tristan Pedersen et al. "An assessment of the performance of scenarios against historical global emissions for IPCC reports". In: *Global Environmental Change* 66.1 (2021).



(a) Population projections of the USA under SSP 1 – 5 scenarios

(b) Gini coefficients for China under SSP 1 – 5 scenarios

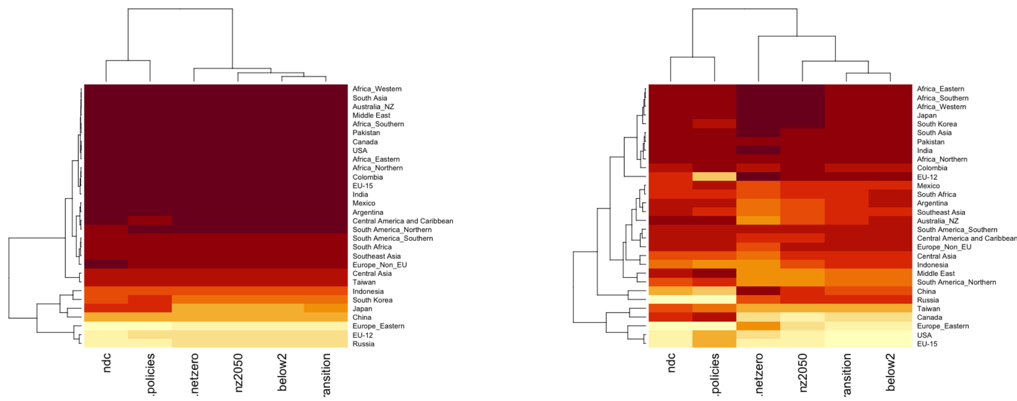
Fig. 3: Population and gini coefficients provided by SSP scenarios

and economic developments over the century are used for all three IAMs. However, while the same SSP input data is used across all three IAMs, how they are modelled within each IAM is different. For example, while population is a fully exogenous input, economic variables such as GDP and GDP growth are exogenous inputs in GCAM, but are treated semi–endogenously for MESSAGEix and REMIND. For the latter two, the GDP projections are are calibrating assumptions on exogenous productivity improvement rates in a no–policy change reference scenario.[23] Hence, they represent general equilibrium effects of constraints and distortions by policies. Despite these difference in the modelling system, the SSP datasets represent key social and economic assumptions that enter all three IAMs exogenously, and are subsequently treated as baseline trends against which the climate and economy interactions are calibrated for projections on the key output variables of interest for the NGFS scenarios.

Since the SSP data on social and economic developments of the global economy are the baseline measure for the NGFS scenario output variables, and since the SSP data is exogenous to the IAM models, the choice of and relationship between the SSP input data and the NGFS scenario outputs represent significant assumptions and uncertainty that drive the differences between NGFS scenario output trends, and subsequently how financial institutions use such trends and projections in their financial decision making. For example, for any exogenous SSP variable, the relationship between the trend in the SSP data and the output data can vary from one of the six NGFS narrative pathways to another. This is illustrated in figure 4, showing the co-variance in the population trends from SSP–2, against the energy demand across all six NGFS narrative pathways by geographic region. From the figure, the difference in the co-variance of population projections against energy

[23] Bertram et al., *NGFS Climate Scenarios Database*, op. cit., pp. 18.

demand illustrates the difference in the extent to which the baseline population is driving estimation of energy demand in the NGFS scenarios. Additionally, this relationship can also vary from the use of one IAM to another.



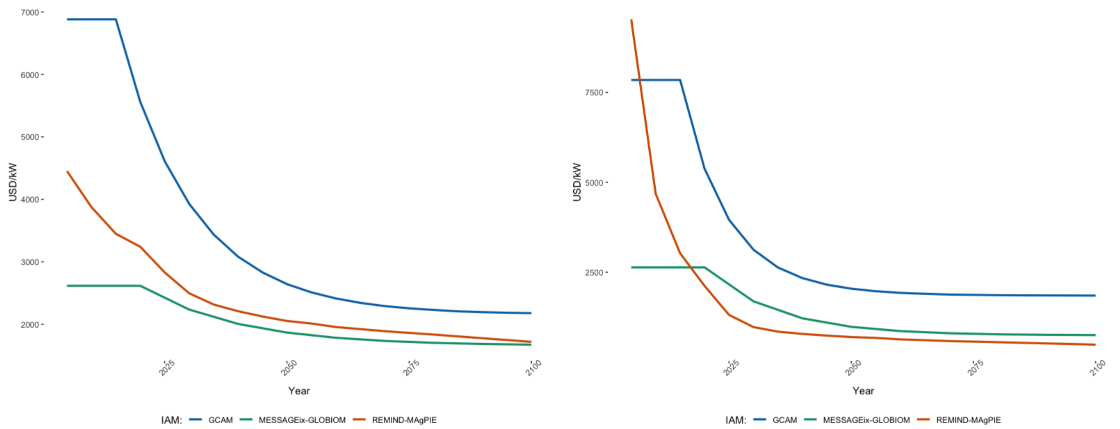
(a) SSP–2 population projections and energy demand to 2100

(b) SSP–2 population projections and emissions from transportation sector to 2100

Fig. 4: Co–variance of SSP–2 population input data with NGFS output data

From the figures, there are clear differences in the correlation of the SSP–2 population input data and the NGFS output data for the energy system variables. These differences are not only observed between one narrative pathway and another, but also from one IAM to another, for the same input variable and the same output variable. This represents significant uncertainty in the selection and analysis of output trends for FIs. As the selection of a set of IAM outputs for analysing transition risk shows significant variability in the assessment of company or portfolio level value at risk, demonstrated from Gasparini et al. (2023), the variability in the relationship between key input variables and output variables indicates significant uncertainty for FIs in the selection of narrative pathways and IAMs. The differences in trends between one IAM and another for the same temperature target or narrative pathway, and the same region and sector is illustrated for technology cost trends to 2100 across GCAM, MESSAGEix, and REMIND in figure 5.

From figure 5, a difference in cost of technology trends under the same narrative pathway and temperature target produces different outcomes. Hence the selection of a particular IAM or pathway can significantly affect FIs in their decision making and decarbonisation strategies. Uncertainty in the IAM trends is compounded by the fact that the three NGFS IAMs use the same SSP data as exogenous inputs for modelling the baseline global social and economic development. The difference in outputs is due to the differences in the model environment of each IAM, however as the



(a) North America: Capital Costs: Wind: Net Zero 2050

(b) North America: Capital Costs: Solar: Net Zero 2050

Fig. 5: Global capital costs of renewable technologies by IAM

SSPs themselves represent significant uncertainty and assumptions on future social and economic development, this uncertainty is further propagated through the variation in outputs from the both the differences between IAM environments and the narrative pathways.

Figures showing the co-variance of SSP input variables compared to the NGFS transition risk output variables demonstrate a difference in the relationship between IAM outputs and how they vary with the baseline exogenous inputs across regions, narrative pathways, and IAMs. Results from this analysis suggest that projections of key variables of transition risk are modelled in different ways depending on the geographic region, the temperature target or narrative pathway, and the IAM. The variability in the outputs, even when holding all else equal, represents extensive uncertainty for practitioners in the use and application of the NGFS scenario data, and for climate scenario in general. Previous analysis in figures demonstrate this variability and uncertainty. However, while this analysis provides a preliminary indication of the variability in the relationship between input and output variables according to co-variance, it is not able to determine the extent to which a particular input variable influences a particular output variable. Additionally, it is not able to compare the relative influence of one SSP input variable from another, or the magnitude the effect.

However, being able to comparatively assess the relative influence of the SSP input variables to the six narrative pathways and the three IAMs used by the NGFS can help FIs to better apply climate scenario data to address their particular needs. For example, scenario outputs such as the energy demand under a stringent carbon pricing scenario can be significantly influenced by input data including the population, GDP, or elasticity of energy demand for various sectors.

Understanding how these inputs are driving the trends in energy demand by sector and by region can help FIs in selecting the best set of scenarios based on their own assumptions, and based on the uncertainties in scenario trends that they are seeking to reduce. Therefore, to measure the relative influence of the set of SSP input data on the primary NGFS output variables of interest for transition risk, this paper employs a method of cumulative distribution sensitivity analysis.

4 Methodology: Sensitivity Analysis

The calculation of how key model assumptions drive differences in scenario outputs raises difficult issues for FIs to understand these differences, since several input variables of the underlying in–sample distributions are identical for all scenario pathways, and since the reported pathways are often deterministic functions. Additionally, issues arise since there are a number of different types of model calculations embedded within each scenario output that are generally unknown.

For example, deterministic impulses or step shifts applied to either a 'given' or conditioning variable, or the initial conditions against a target variable. This would be the case for scenarios such as a specific global average temperature target at a certain time horizon. Second, stochastic shocks from some assumed distribution can be used to perturb either the initial conditions or the conditioning variable. How stochastic shocks are modelled depends on the type of IAM being used, and how the parameters are set to evolve in the model, such as the rate, timing, and stringency of a carbon tax, or the rate, timing, and evolution of technologies. Third, adding random numbers drawn from the estimated in–sample error distribution to the scenario, but not the baseline, would be a further alternative. All of these choices in the initial modelling conditions would vary by the type of IAM being used and by the assumptions of the particular narrative pathway, however they would not depend on the parameters being set. The result is that a set of different outputs for each narrative pathway and IAM will result from all these processes, which define the uncertainty around each scenario trajectory.

Hence, by analysing differences in the trends of output variables against the identical input variables across scenarios and IAMs, a relative measure of the drivers of uncertainty according to variability can be calculated for each climate scenario. Having a relative measure of how one input variable drives uncertainty in a particular scenario output variable can help FIs and other institutions determine the best pathways or output data to use for their own analysis, based on the particular beliefs of the future, and their particular portfolios. For FIs using climate scenarios for financial analysis, understanding the drivers of uncertainty for key transition risk output variables according to a key set of input variable assumptions can help FIs to more efficiently determine the subset of model parameters that best aligns with their own assumptions of the future or their strategic priorities.

For analysis comparing differences in model output trajectories according to model inputs, this paper employs a method sensitivity analysis. Sensitivity analysis is a set of techniques that are used to address questions related to the relationship between input and output variables in a static or dynamic simulation model, where the model is a numerical procedure used to simulate the behaviour of a system by solving a set of equations. This includes methods of quantifying which input factors cause the largest variation in the output, which input factors have a negligible effect on the output, and which interactions amplify or dampen the variability in the output.[24]

In predictive or forecast scenario models, there are always degrees of uncertainty in the model environment over the types of dynamics that are established, such as the various choices being made in determining model parameter values. To this extent, methods of sensitivity analysis can consider the influence of model inputs on variation in the outputs to provide quantitative metrics and indices that describe model behaviour and assumptions. By having a comparable and quantitative measure by which a variety of IAM outputs can be compared, this allows for better understanding of the key assumptions being made in the scenario forecasts of NGFS, where differences between the three IAMs being used are not well established in terms of differences in the output trajectories.

For the purposes of analysing the entire distribution of model outputs, instead of only the variance in outputs, a cumulative distribution based GSA method is used (PAWN). The PAWN method allows for a generic dataset to be applied to its analysis of parameter ranking, and requires fewer tuning parameters which makes the approximation procedure easier to evaluate.[25] Since the analysis is focused on comparing a set of inputs and outputs that have already been generated from the NGFS IAMs where the full set of parameters in each model are not known, PAWN offers the most flexible method for conducting sensitivity analysis for generic datasets in this case. In addition, the method provides consistent results with other GSA methods that require more specific tuning parameters that have to be explicitly observed, or where variation in outputs is observed from the data generating process itself.

The method assumes a normal input-output relationship, $y = f(x)$, where $x = |x_1, x_2, x_3 ... x_M| \in \chi \subseteq R^M$ input factors and $y \in R$ is a scalar output variable. The goal of GSA is to quantify the relative contribution of variations in each input factor x, to the variability of

[24] Francesca Pianosi et al. "Sensitivity analysis of environmental models: A systematic review with practical workflow". In: *Environmental Modelling and Software* 79 (2016), pp. 214–232.

[25] Francesca Pianosi and Thorsten Wagener. "Distribution-based sensitivity analysis from a generic input-output sample". In: *Environmental Modelling and Software* 108.1 (2018), pp. 197–207.

the output y. A quantitative measure of such relative contribution is expressed by the value of a sensitivity index S. typically ranging from 0 to 1.

The key idea of distribution-based methods is that the influence of an input factor is proportional to the amount of change in the output distribution produced by fixing that input. The sensitivity of x is measured by the difference between the unconditional distribution of y, which is induced by varying all input factors simultaneously, and the conditional distribution that is obtained by varying all inputs but x. The distinctive feature of PAWN is that, in contrast to other methods, it uses conditional and unconditional cumulative distribution functions of the output instead of the probability density functions. The PAWN sensitivity index for the $i-th$ input factor is defined as:

$$S_i = stat_{x_i} KS_{x_i}(x_i), KS(x_i) = max_y |F_y(y) - F_{y|x_i}(y|x_i)| \tag{1}$$

Where $F_y(y)$ and $F_{y|x_i}(y|x_i)$ are the unconditional and conditional cumulative distribution functions of the output y, and $stat$ is a statistic (maximum, median, or mean). The maximum absolute difference in equation **??** is Kolmogorov-Smirnov (KS) statistic, which is widely used as a measure of distance between CDFs. From equation 1, the value of the sensitivity index S measures the relative influence of an input variable on the amount of change in the output variable distribution. For each S_i, the greater the value of S indicates the greater the influence input variable i has on the output variable from the IAM. Equation 1 is subsequently applied to the set of exogenous variables that are generally assumed social and economic pathways by the NGFS. By applying equation 1 to each of the main set of social and economic variables from the SSP dataset used by NGFS, the sensitivity index measures the relative influence of each input variable against some of the key output variables from the NGFS scenarios that are used for assessing transition risk: carbon sequestration, technology costs, and energy demand.

5 Analysis: Carbon Sequestration

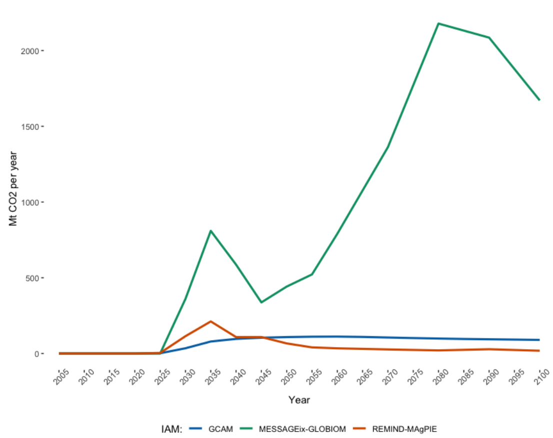
As previously cited in table 1, Monasterolo et al. (2022) have identified four risk drivers to transition risk severity, including the timing of policy response, the level of policy coordination, the pace of technological change, and the availability of carbon sequestration and carbon removal technologies.[26] The use of carbon removal technologies is a significant transition risk factor for FIs since uncertainty in the availability or impact of carbon capture and storage (CCS) translates directly

[26] Monasterolo, Nieto, and Schets, "The good, the bad, and the hot house world: Conceptual underpinnings of the NGFS scenarios and suggestions for improvement", op. cit.

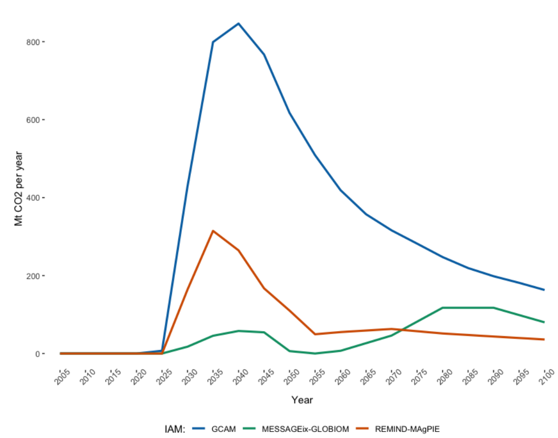
into the amount of net emissions for a firm or company, and the amount of emissions that the company needs to cut. This translates directly into a FIs decarbonisation target setting, mitigation trajectory, and financial risk, since the greater the availability of CCS means the more gradual the phase out of fossil fuels across various sectors, and the lower the risk to the FI that has invested in the company.

NGFS provides only two pathways for the availability of CCS, which is represented by the amount of carbon that is sequestered per year, measured in metric tons, and projected out to 2100.[27] The assumptions are either a medium or a low usage, which corresponds to the amount of carbon per year. The NGFS separates the amount of carbon removed from CCS by sector, such as from fossil fuels or from the industry sector. Figure 6 shows differences in the trend of the amount of carbon removed under each IAM used by the NGFS for the same temperature target, even if the same input data is used, and the same assumptions on the future availability of CCS is made. The figure shows how the estimated amount of carbon that Europe and China can sequester is different for each IAM, despite the fact that the trends are based on the same objective of reaching a global net zero by 2050. This indicates that the choice of which model is used completely changes the view of the future evolution of the amount of carbon sequestration. This subsequently makes any choice and application of one pathway of carbon sequestration or another entirely unreliable, without a better sense of the underlying factors that are driving such differences in variable trends for the same policy ambition of reaching net zero by 2050.

Since all of the IAMs used by NGFS use the same key input data assumptions from the SSPs, which



(a) Europe: Carbon Sequestration: Fossil Fuels: Net Zero 2050



(b) China: Carbon Sequestration: Fossil Fuels: Net Zero 2050

Fig. 6: Carbon sequestration by IAM under same narrative pathway

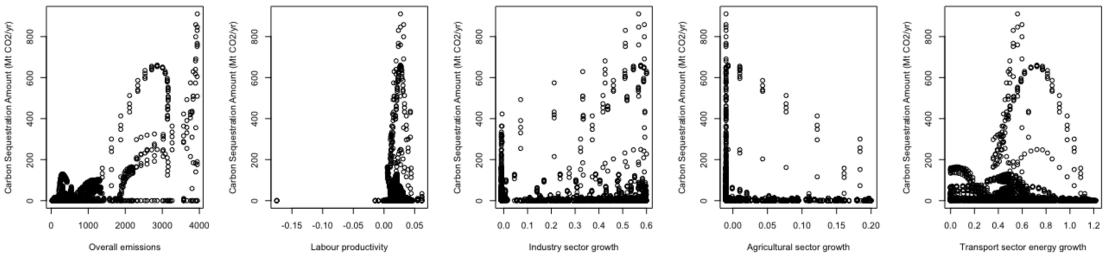
[27]The timing interval is different under each of the three IAMs used by the NGFS. For all three IAMs, the time interval is every 5 years until 2050. Then after 2050, the time interval is every 10 years under REMIND and MESSAGEix, but continues for every 5 years for GCAM to 2100.

are the SSP–2 middle of the road scenario, then comparing the variability in NGFS outputs of carbon sequestration against the standard set of SSP variables that are input across all three NGFS IAMs shows the relative influence that one SSP assumption has on the expected amount of carbon sequestration. Applying the model of sensitivity analysis shown in equation 1, the input variables $x_{i,n,t}$ are the set of thirteen variables taken from the SSP-2 scenario, as previously discussed in section 3 on the SSP input variables for each region n and time period t.[28] The set of thirteen inputs are compared according to the conditional cumulative distribution of the scenario output variable of interest, $y_{n,t}$ for each region n and each time period t. In this case, the regional and temporal output variation in the amount of carbon sequestered is compared against the set of thirteen input variables to observe the sensitivity of the projected amount of carbon sequestered bases on the set of thirteen social and economic projection assumptions from SSP–2.

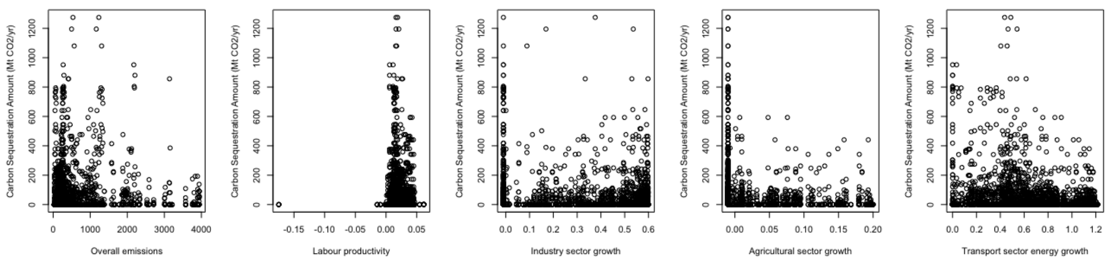
The output variable is taken directly from the NGFS scenario database as the total amount of carbon that needs to be sequestered from the fossil fuel sector per country in Mt CO2 per year. An example of the output trends that are used in the sensitivity analysis are shown from figure 6. The figure illustrates the variation in the amount of carbon sequestration in the fossil fuel sector in Europe and China over time under each of the three IAMs. Hence, this study exploits the variation in NGFS output trends according to regional, temporal, and sectoral variation of the output variable. Therefore, the variation in the inputs is taken from the geographic and temporal variation derived from the distribution of the SSPs relative to the output variable of interest. Since the variation is not derived from the input parameters, but in the simulation procedure used to compute $y_{n,t}$ from $x_{i,n,t}$, the PAWN method of sensitivity analysis is best suited for this analysis. To broadly observe the extent of the variability between SSP input variables and the NGFS outputs of carbon sequestration under each of the three IAMs, figure 7 shows the patterns in the relationship between five of the thirteen SSP input variables against the projected amount of carbon that can be captured under each IAM. Each scatter plot shows the independent input variable on the x–axis compared to the dependent output variable on the y–axis. The y–axis is the amount of carbon that is expected to be sequestered, measured in MT of CO2 per year, compared to a set of key social and economic input variables from the SSP–2.

From left to right, figure 7 shows national–level emissions, labour productivity, industrial sector growth, agricultural sector growth, and transport sector growth. From the figures, there is a clear difference in the relationship between the input variables and the amount of CCS. For example, in

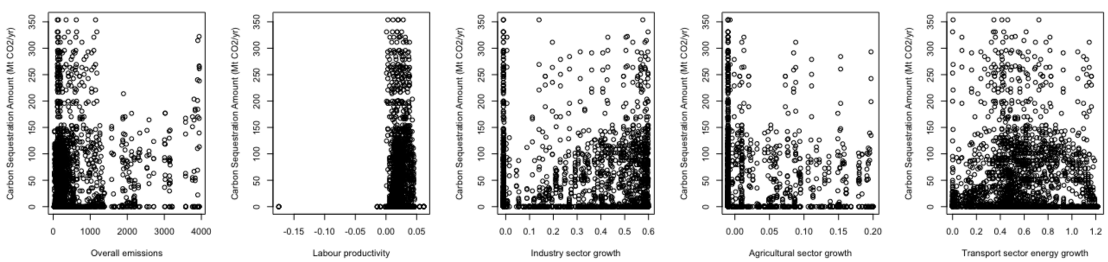
[28] The thirteen variables included do not incorporate the full set of input variables that are used in each of the IAM models from the NGFS, but include some of the key exogenous social and economic trend variables from the SSP 2 scenario that are used as standard inputs across all three of the NGFS IAMs.



(a) GCAM



(b) MESSAGEix-GLOBIOM



(c) REMIND-MAgPIE

Fig. 7: Scatter plots of carbon sequestration projections compared to SSP input variables

the case of overall emissions in the far–left panel under each of the three IAMs, the relationship between the overall level of emissions and the amount of carbon sequestered is completely inverse. Under GCAM, the pattern shows that as the overall amount of emissions increases, the amount of carbon sequestered increases. Conversely, REMIND and MESSAGEix show the opposite pattern where the lower the level of overall emissions input into the model, the higher the amount of carbon that is sequestered from in the fossil fuel sector. Similar patterns are also evident across other panels. REMIND shows the strongest relationship of higher rates of industrial sectoral growth with higher amounts of carbon sequestration. MESSAGEix shows a similar but lower relationship, whereas GCAM does not show any pattern of a relationship with industrial sector growth and carbon sequestration. Agricultural sector growth shows evidence of a relationship between higher agricultural sector growth and lower amounts of carbon sequestration under GCAM and REMIND, but this is not shown for MESSAGEix. In the case of transport sector energy growth, GCAM shows a clear trend in higher rates of transport energy growth being related to higher amounts of carbon sequestered. However, there is not evidence of a pattern to transport energy growth and the amount of carbon sequestered under REMIND or MESSAGEix.

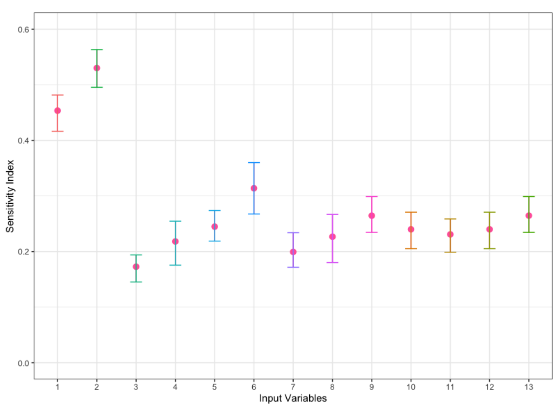
Patterns in the relationship between the standard set of SSP input variables and the trajectories of carbon sequestration under the three different IAMs demonstrate that these models assume completely different relationships between input variables. In the case of projections on the amount of carbon sequestered to 2100, the three IAMs provide different trajectories based on different social and economic assumptions. Observing patterns from figure 7 show how some input variables are positively related to the amount of carbon sequestered, and others are negatively related. Differences in patterns reflect differences in the underlying modelling techniques and assumptions for each of the three IAMs used by the NGFS, such as assumptions on whether or not higher levels of emissions should be positively or negatively related to the amount of carbon sequestered.

While figure 6 shows different trends in the amount of carbon sequestered under the three NGFS IAMs, it is not well known where these differences in trajectories come from. This makes the application of forecast trends by practitioners similarly difficult to understand, or to consistently apply. While it is assumed that each IAM models the interactions of input variables differently, it is not well understood what those modelling practices are, or how assumptions in modelling interactions affect particular output variables of interest. Findings from this paper provide evidence of how the relationship in forecast trends of carbon sequestration are related to other key input variables to illustrate some of the underlying assumptions that drive differences.

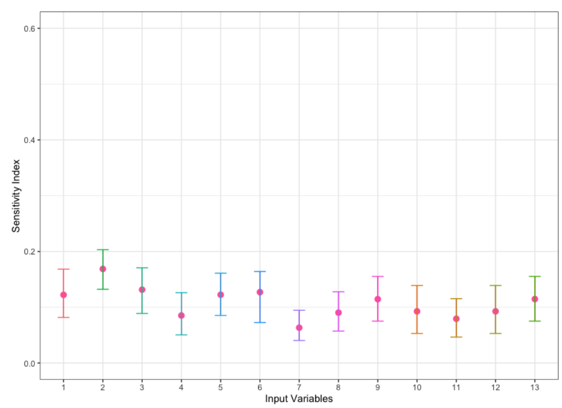
For example, the amount of carbon sequestered in China in figure 6b is projected to be greatest under GCAM, and for Europe in figure 6a the greatest amount of carbon sequestered is projected under MESSAGEix. Evidence from the scatter plots in figure 7 suggests that the large amount of sequestration from China is due to the large amount of overall emissions from the country. In contrast, the larger amount of sequestration for Europe is more likely related to growth in the industrial sector. Understanding these modelling assumptions based on the key input variables that are consistently applied across IAMs, can help practitioners in model selection and narrative pathway based on a better understanding of how trends in these key variables are assumed to unfold in the future.

However, evidence illustrated in figure 7 is more descriptive rather than quantitative, and only includes a subset of the key social and economic input variables that have been included in the analysis. While previous evidence shows that different IAMs assume completely different and inverse relationships between input and output variables, analysis has not established the relative influence of each of these input variables on the key output variable of interest. Therefore, in order to more formally measure the relative influence of each input variable in driving the uncertainty of the scenario projection, the sensitivity index previously shown in equation 1 is applied to the same set of data shown in figure 7. Figures 8 shows the sensitivity indices of the relation between the amount of carbon sequestered to each SSP input variable of interest.

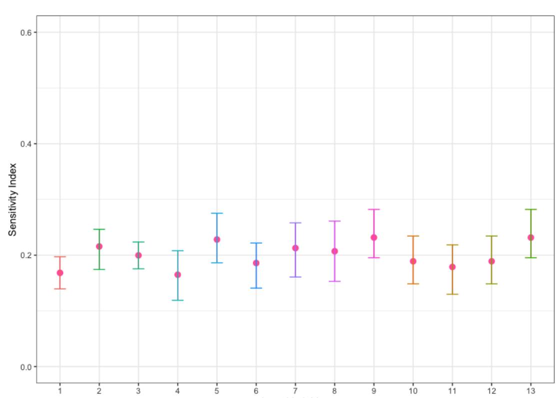
From figure 8, the results show the sensitivity of each input variable from the SSPs to the climate scenario output variable of the amount of carbon that can be sequestered using CCS technology for the full set of 13 input variables taken from the IAMs. Comparing the three different charts, one for each of the three IAMs used by the NGFS, the results demonstrate a difference in the relative sensitivities of each input variable driving differences in the projected amount of carbon that can be captured by CCS technology. The input variables are arranged on the x–axis as follows: 1 overall emissions, 2 GDP, 3 land use changes, 4 GDP growth rate, 5 GDP per capita, 6 population, 7



(a) GCAM carbon sequestration by sector



(b) MESSAGEix-GLOBIOM carbon sequestration by sector



(c) REMIND-MAgPIE carbon sequestration by sector

Fig. 8: PAWN sensitivity analysis of carbon sequestration by IAM

labour productivity, 8 industrial sector change, 9 building growth, 10 agricultural sector change, 11 construction sector change, 12 mining change, and 13 transportation sector change.

Overall, the chart shows that, for all the social and economic variables from the SSPs that have been included, projections from GCAM are more sensitive to the SSP data than the projections from either MESSAGEix or REMIND. This suggests that for the amount of carbon captured under different IAMs, trends from GCAM are mostly driven by assumptions on the growth in population or GDP. In contrast, for MESSAGEix or REMIND with low sensitivity indices across input variables, the capacity of carbon sequestration is not primarily driven by social and economic factors.

More specifically, GCAM shows that the input variables 1, 2, and 6 for overall emissions, GDP, and population are the largest variables that are distinctively influencing GCAM's projections of carbon sequestration. In contrast, these three variables do not have as high of a sensitivity index under MESSAGEix or REMIND, thus indicating that they are not as strong of inputs driving the projections of carbon sequestration. For MESSAGEix and REMIND, none of the input variables included show a significantly stronger role in influencing the trends of CCS projections, instead they all appear to have a similar level of influence on the estimated amount of carbon sequestration.

Differences in carbon sequestration projections shown in figure 6 under the same narrative pathway, but simulated under different IAMs are shown to be the result of different modelling techniques and assumptions in the IAMs. Since the exact process of creating the projections is not well–established, and hence the key assumptions are not well–known, the PAWN method to sensitivity analysis provides a comparative assessment of the relative influence of thirteen exogenous input variables that have been standardised by NGFS across all three IAMs. Results from figures 7 and 8 show the differences in how key input variable assumptions drive the distribution of projected trends under each IAM. While it would be expected that IAMs use different modelling techniques that subsequently lead to some variation between in the output variables, evidence shown here has demonstrated not only the vast difference between output trends between IAMs, but also the large extent to which assumptions on the relationship between input and output variables are modelled in completely opposite ways. This has significant implications for the trust, credibility, and applicability of key IAM output variables for use by practitioners.

For practitioners and policymakers applying trends on key variables such as the availability of CCS technology to remove or sequester carbon, the choice of one IAM trend or another under the same policy ambition can often be made for unknown reasons, since it is not known or well established why trends under the same temperature target or policy ambition differ. This can have significant implications for assessing alignment, resilience, and risk, since practitioners can select the IAM projection that is most favourable for their own purposes under a specific target, and since the reasons for those differences are not well known. Analysis shown here provides evidence that some of the differences in IAM projections are related to the vast difference in the underlying relationship between social and economic input variables and the output variables. Understanding these differences can help practitioners in the selection of IAM projections of key variables, and provide greater transparency in the evaluation of alignment, resilience, and risk for all types of organisations.

6 Analysis: Capital Costs

In addition to carbon sequestration, other variables of interest for transition risk are the rate and degree of technological change, which can be embodied from the capital costs of certain types of renewable technologies. The price of renewable energy technologies is a significant risk driver for FIs since uncertainty in the price of renewables significantly affects how companies develop decarbonisation strategies in their portfolios. Decisions about how and when to decarbonise the global energy system are highly influenced by estimates of the likely costs, where the costs and deployment will evolve over time due to variables including the rate of innovation, competition, public policy, concerns about climate change, amongst several others factors. Several models have attempted to capture these among other variables that theoretically influence projections on the capital costs of renewable versus non–renewables, and showing a wide range in trends based on the inclusion or exclusion of variables that are factored into cost projections.[29]

The difference in the cost of these technologies can have significant implications for FIs in their investment and decarbonisation strategies based on the price of renewables. Studies on the variability in scenario projections of the cost of energy are shown to significantly affect companies' valuations based on different projections.[30] Given the wide variety in outcomes of capital costs based on the same input data for each of the three IAMs, including the same social and economic assumptions from the SSP–2 middle of the road calibrating data, this leads to extensive uncertainty in the use, reliability, or confidence in the scenarios.

The NGFS scenarios provide projections on capital costs of renewable technology measured in the price per kWh projected to 2100. As previously shown in figure 5, the trends in capital costs of renewables show a different trajectory according to each of the three IAMs used by the NGFS

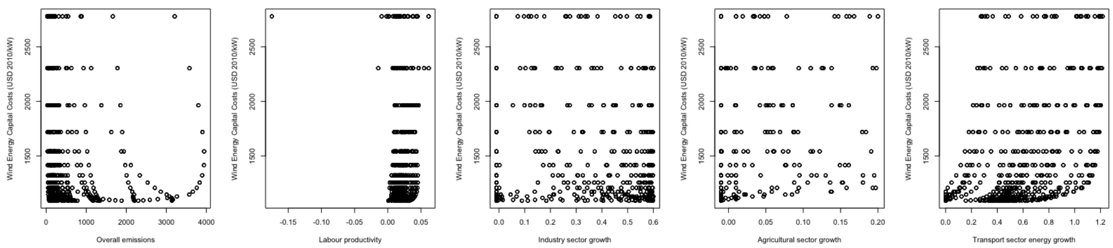
[29] Way et al., "Empirically grounded technology forecasts and the energy transition", op. cit.
[30] Gasparini, Baer, and Ives, "A re-evaluation of the financial risks of the net zero transition", op. cit.

for the same policy ambition, the same renewable technologies, and the same region. Therefore, using the same method of sensitivity analysis applied for carbon sequestration, the variability in the scenario outputs of capital cost for renewables is observed from the differences in trends for each region and time period. The same set of exogenous input variables taken from the SSP–2 scenario, as discussed previously in section 3 are compared against the scenario output trends in capital costs for each region and time period as shown in figure 9. Sensitivities are calculated from equation 1 by comparing the set of thirteen inputs $x_{i,n,t}$ for each i input, in region n, and time t, against the single scenario output variable $y_{n,t}$ for the capital costs of renewables.

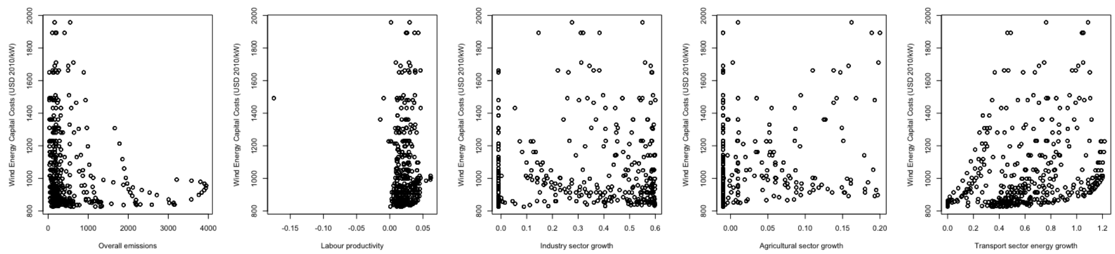
Similar to previous analysis on carbon sequestration, capital costs of renewable technologies is compared against the same set of thirteen exogenous SSP input data projections for forecasts to 2100. Figure 9 shows the relation of capital cost projections for wind energy in relation to five of the thirteen SSP input variables that are treated as exogenous inputs to capital costs. The input variable projections included are: 1 Overall emissions, 2 GDP, 3 land use change, 4 population, and 5 transport sector energy growth. The plots show how the NGFS output of the projections of capital costs of renewables varies with each input variable from the SSP. Each data point represents the capital cost for onshore wind in a particular region and year to 2100.

From the first panel, overall emissions and the cost of wind energy appears to show a much stronger negative relationship under REMIND, with little relationship less distinct evident under MESSAGEix. Second, a similarly stronger trend is observed with GDP in panel 2 for REMIND, but is not evident for GCAM and MESSAGEix. Third, the relationship between population and the capital cost of wind shows no distinctive pattern with GCAM in panel 4, however there is strong, negative relationship with population in MESSAGEix and REMIND. Overall, evidence shows that even when NGFS uses the same SSP input variables for three different IAMs, each model assumes fairly different relationships between input variables, and how they expect each to relate to forecast trends on variables of interest.

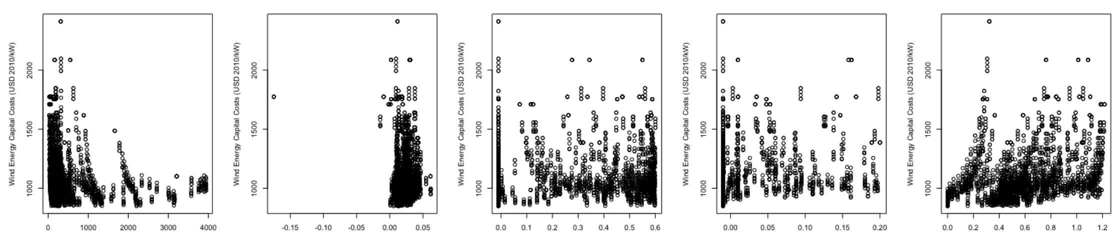
Considering differences in trends of capital costs in figure 5, observing patterns in the relationship between inputs and outputs of IAMs can be understood according to assumptions in the modelling behaviour of the relationship between variables, as shown in figure 9. For example, REMIND shows a fairly distinctive trend compared to the other two IAMs with the most rapid decline and the lowest level of capital costs for wind power in figure 5b. When comparing this trend to differences in the modelling behaviour and assumptions observed in the scatter plots from figure 9, this suggests that the rate of decline and the level of the costs for renewables could be related to the modelling assumptions of REMIND in relation to overall emissions, GDP, and population, as shown and discussed in plots 1, 2 and 4 from figure 9. From these plots, REMIND shows a much stronger relationship to these SSP input variables compared to either GCAM or MESSAGEix. Hence, when understanding differences in projections of key variables of interest, such as the cost of renewables, evidence from figure 9 illustrates the differences in the underlying model assumptions between the IAMs, based on how they relate to the standard set of SSP input variables.



(a) GCAM



(b) MESSAGEix-GLOBIOM



(c) REMIND-MAgPIE

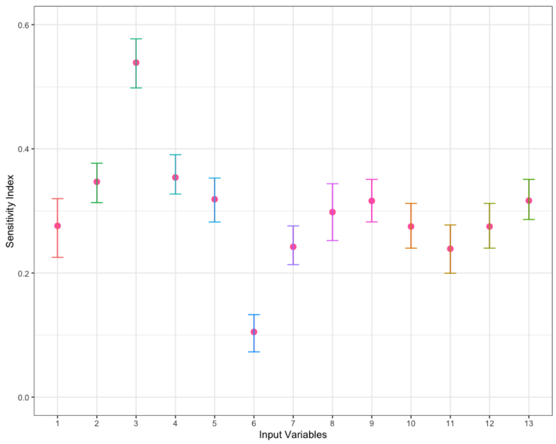
Fig. 9: Scatter plots of capital costs for onshore wind projections compared to SSP input variables

Previous analysis from figure 9 shows different patterns in the relationship between input and output variables that provides qualitative evidence of differences in IAM assumptions. However, it does not establish the relative influence of each input variable in driving output trends to establish the significance of the relationship. Therefore, to quantitatively assess the relative influence of each of the thirteen input variables that have been compiled in relation to the capital costs of renewables, PAWN sensitivity analysis is applied to the set of SSP input variables. The results of how sensitive projections of capital costs are to each SSP input variables are shown in figure 10. The thirteen variables that are shown on the x–axis are: 1 overall emissions, 2 GDP, 3 land use changes, 4 GDP growth rate, 5 GDP per capita, 6 population, 7 labour productivity, 8 industrial sector change, 9 building growth, 10 agricultural sector change, 11 construction sector change, 12 mining change, and 13 transportation sector change.

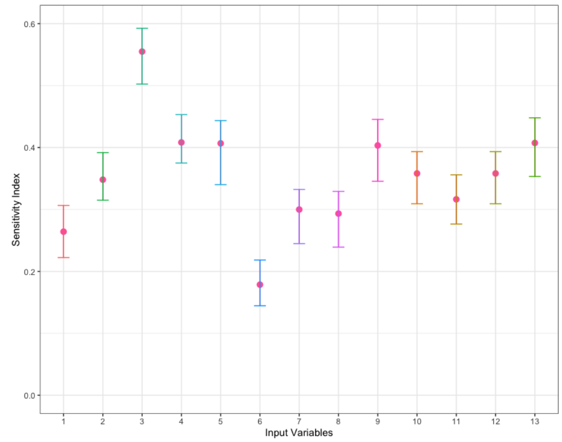
In contrast to analysis on carbon sequestration where input variables were not distinctively influential under MESSAGEix and REMIND, but only for GCAM, in the case of capital costs for renewables, all three IAMs show the distinctive influence of some variables over others. From figure 10a all three show similar patterns of sensitivity, but some input variables are more distinctive drivers, while others are less influential in the output trends. First, all three IAM trends are most sensitive to land use changes as the biggest driver of capital costs. Second, MESSAGEix and REMIND show that GDP trends matter more to capital costs than under GCAM. The GDP growth rate appears to have the largest influence on capital costs under MESSAGEix. Third, population has the lowest effect on capital costs under GCAM and MESSAGEix, but appears to have more of an influence under REMIND.

Evidence in figure 10 reveals several key features about the underlying assumptions driving capital costs projections in the three IAMs. Findings show that across all three IAMs, the input variables that are the most influential for capital cost projections are the macro–economic variables such as GDP, growth rates, and population. Amongst the macroeconomic variables, each has a different influence in the trend in capital costs, where the growth rate of GDP is more influential than the overall level of GDP under MESSAGEix. However, the inverse is true for REMIND.

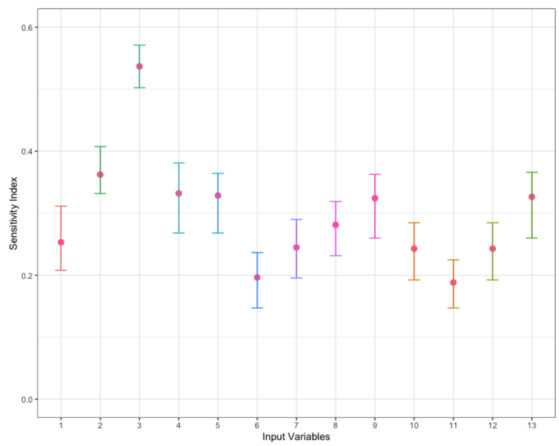
When considering evidence from figure 9 showing the different patterns in the relationship between input variables according to IAM, along with the results of their relative sensitivities from figure 10, this helps explain differences in IAM trajectories for key output variables under the same narrative pathway. The stronger relationship between the input variables for overall emissions, GDP, and population under REMIND is a more significant driver of capital cost trend for REMIND relative to the other IAMs, as shown in figure 10. For example, while variable 3 for land use changes in figure 10 is the most significant driver of the capital cost projection across all three IAMs, GDP is the second most sensitive for REMIND, but not for the other two. GDP also shows a distinctive negative relationship with the capital costs of wind energy under REMIND, which is not observed for GCAM or MESSAGEix. Additionally, variable 6 for population shows a more distinctive pattern with capital costs under REMIND than for the other two IAMs, and has a higher sensitivity to the output variable compared to the other two IAMs. Therefore, taken together, differences in rate of



(a) GCAM capital costs of renewables



(b) MESSAGEix-GLOBIOM capital costs of renewables



(c) REMIND-MAgPIE capital costs of renewables

Fig. 10: PAWN sensitivity analysis of capital costs of renewable technologies by IAM

change and level of projected capital costs of wind in figure 5b is likely the result of the particular modelling assumptions of REMIND, which is driven by assumptions on the relationship between overall emissions, GDP, and population.

Various studies exploring the costs of renewable versus non–renewable energy technology have debated the merits of some data modelling techniques compared to others.[31] Instead, this study simply assesses the relative influence of some key input variable in order to determine the social and economic assumptions being made in driving forecasts on the capital costs of renewables. When applying IAM forecast trends, analysis from figure 10b provides a better understanding of how projections of capital costs are modelled according to relationships with social and economic input data, which can help practitioners in differentiating IAM trends for use in their own analysis on the basis of beliefs, priorities, or assumptions about the likely drivers of costs of renewables. If

[31] Elena Verdolini et al. "Future prospects for energy technologies: Insights from expert elicitations". In: *REview of Environmental Economics and Policy* 12.1 (2018), pp. 133–153.

FIs assume or believe GDP as being a primary driver of capital costs for renewables, then evidence from figure 10b suggests they should use the projections provided by MESSAGEix or REMIND rather than GCAM. If on the other hand FIs believe that GDP per capita will not drive the costs of renewables as much as the rate of growth in GDP, then they should use trends provided by GCAM.

For practitioners and policymakers using NGFS scenarios for analysis including target setting, alignment, and risk assessment, the choice in climate scenario and IAM can have significant implications, as illustrated by the range in projected trends of key variables such as carbon sequestration or renewable technologies. While IAMs project different trends for key variables, the reasons for those differences are not well known. While it is expected that different IAMs should produce different trajectories due to differences in the modelling techniques, in many cases those differences in trends can be quite large, and can have significant impacts on how companies and FIs assess their climate strategies.[32] Therefore, it is important for practitioners to be able to identify some reasons and justifications for choosing one scenario trajectory over another.

Analysis presented on carbon sequestration and capital costs of renewables provides evidence of differences between IAMs under the same temperature target based on differences in the relationship of output variables for the same set of input variables. Without a better understanding of what is driving the differences, the selection of one IAM over the other by FIs and practitioners cannot be consistently applied or evaluated when analysing climate strategies, since so little is known about what is driving the differences in trends between IAMs. Findings from scatter plots and sensitivity indices provide a better understanding of the input variables that are driving trends, as well as key assumptions on the relationship between inputs and outputs. Understanding both the degree to which inputs are driving outputs, and the assumptions on the type of relationship, such as positive or negative relationships, provides greater information and insights for practitioners when choosing different output trajectories. Understanding the assumptions being made or the key drivers of trends helps practitioners in model selection, and in the consistent application of IAM trends for further applications based on a better understanding of how each IAM projection is designed, what it is based on, and how best it should be applied for purposes such as target setting, alignment, and risk assessment.

7 Conclusion

This paper considers inferences made on the differences between climate scenario trajectories when using estimated models of an unknown data generation process. For multivariate models such as

[32] Gasparini, Baer, and Ives, "A re-evaluation of the financial risks of the net zero transition", op. cit.

those used by the NGFS, results show that there are key differences in the underlying assumptions in IAM models when projecting key climate and economic variables used by financial institutions, such as the amount of carbon sequestration and the capital costs of renewable energy. Analysis using the PAWN sensitivity method show that there are several differences in the relative influence of social and economic input variables in driving projections of key outputs, even when looking at the same policy ambition, the same narratives, and the same regional geography.

This has significant implications for practitioners using climate scenarios provided by NGFS, since there are several models, scenarios, and pathways available, but the choice in applying one scenario trajectory over another is not well established or well understood. As a result, for financial institutions and practitioners that are applying climate scenarios for the development of climate strategies, they are often inconsistently applied and are not comparable between institutions, since they often assume completely different trajectories of how the economic transition will unfold, the underlying reasons and assumptions for which are not known.

NGFS provides a wide range of data and variables for climate scenario forecasts, however the underlying differences in how the three IAMs produce outputs is assigned broadly to differences in the modelling techniques. MESSAGEix–GLOBIOM and REMIND–MAgPIE are general equilibrium models that solve with an inter–temporal optimisation algorithm. In contrast, GCAM is a partial equilibrium model of the land use and energy sector.[33] Additionally, the models also differ in terms of the coverage of mitigation options in the energy system based on the assumptions in technology costs, efficiencies, and rate of innovation. Differences in modelling techniques help explain the fact that there are different trajectories for the same narrative pathways, however it does not provide enough information to explain differences for each IAM output variable.

Drawing on the PAWN method of sensitivity analysis, this paper has sought to provide a measure of comparability between climate scenarios based on differences in the key underlying assumptions based on social and economic input data. Taking a comparison of two key scenario outputs of interest for financial institutions, this paper shows how, in addition to the differences in the explicit modelling techniques between IAMs, differences in assumptions can be observed in the sensitivity of key output variables to the same set of SSP inputs. While MESSAGEix–GLOBIOM and REMIND–MAgPIE are both general equilibrium models, analysis has demonstrated that they differ in the relationship between key input assumptions and output projections. Understanding

[33]Bertram et al., *NGFS Climate Scenarios Database*, op. cit.

how each IAM treats the same set of social and economic assumptions provides a basis for practitioners to distinguish and select between one scenario output over another, based on their own preferences or beliefs on the future development of key variables of interest.

Although this paper has sought to provide a measure of comparability to distinguish climate scenarios, the analysis is not comprehensive. Using PAWN sensitivity analysis allows for a comparison of the relative influence of a standard set of SSP input variables across IAM outputs, however the analysis does not fully explain the relationships between input data and how it shapes differences in outputs. The IAMs are highly complex in the relationship between input and output variables for the creation of scenario projections. They are data driven models that are intended to capture all of the key variables and interactions to model the global climate and economy. Hence, establishing how one or more input variables drives a particular output is difficult to isolate and establish clearly, especially in multivariate models where systems vary simultaneously. When models include multiple covariates together with variables that are perturbed by scenario analysis, then inferences on the difference in scenario outputs depends on the relationship among all covariates. In the case of the NGFS scenarios, this would be the case between the exogenous SSP conditioning variables and adjustment made to policy variables.

Model–based scenarios can vary in unknown ways with unknown omitted influences and parameter changes. This makes any study that attempts to causally assesses how inputs drive variance in outputs difficult to conduct for a single climate scenario, and potentially lacking in comparability when done across a set of scenarios that are modelled differently. While studies explaining the differences in IAM sensitivities between input and output variables would be a valuable topic of investigation, this paper has only sought to provide a comparable measure of climate scenarios based on the relationship between input and output data.

Additionally, as IAMs include several systems of inputs and outputs, such as the energy, water, land use, agriculture, economy, and climate system, it is not possible to include all input variables into this analysis. While the inclusion of all input data into the sensitivity analysis would be the most accurate way to establish the relative influence of input variables driving output trajectories, there are simply too many variables to incorporate, and observing the relative impact of one variable over another would be difficult to distinguish from the full set of variables. Instead, this paper has focused only on the key social and economic variables from SSP–2, which are more easily identifiable in the IAM as they are key assumptions on future trajectories that enter the model exogenously, and since they are consistently applied as the baseline for the three IAMs. Despite differences in modelling techniques and behaviours between IAMs, since the SSP data is the theoretical baseline trajectory for all three, the input data can consistently be applied for sensitivity analysis.

While this study is not an exhaustive analysis of the influence of model inputs on outputs, findings from the key social and economic input variables from the SSPs allows for a more easily understandable and comparable assessment of differences in climate scenario trajectories. Being able to compare scenario inputs with outputs according to the relative influence of social and economic assumptions will hopefully enable financial institutions and practitioners to better distinguish, identify, and select scenario variables as it applies to financial analysis of sustainability strategies, alignment, and risk, by having a better sense of the social and economic assumptions underlying climate projections.

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