Value in motion: Methodology

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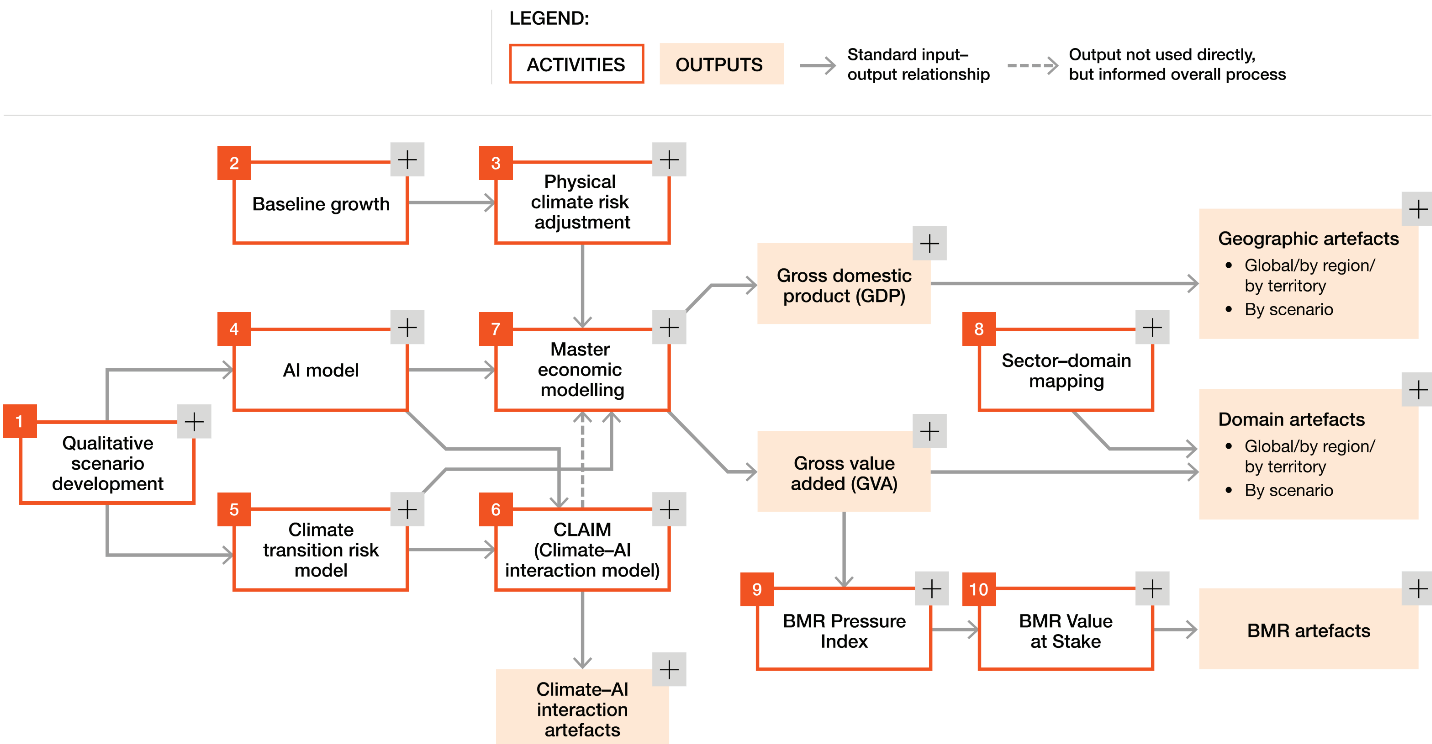
Methodology framework



Source: PwC research and analysis

Activities

For explanation of the Activities, please see the rest of this document.

Outputs

Gross domestic product (GDP): The total value of goods and services produced within a country's borders, serving as an indicator of economic health and allowing for comparisons among nations and regions, as well as global aggregation.

Gross value added (GVA): The total value of goods and services produced by an economic sector, such as agriculture, manufacturing or financial services. GVA provides insights into the contribution of that sector to overall economic output, and enables reaggregation into domains.

Geographic artefacts: More specific GDP estimates at the regional and country level, differentiated by scenario.

Domain artefacts: Domain-specific estimates of the magnitude, growth potential and uncertainties for each of the domains of growth, measured in GVA terms, at the global, regional and country level, used to evaluate performance potential under each scenario.

BMR artefacts: Economic value at stake per unique sector–geography pairs due to reinvention pressure over the next one to two years, expressed in US$.

Climate–AI interaction artefacts: Estimated change in energy efficiency, renewable energy ratios, data centre energy consumption and total energy consumption, across both renewable and non-renewable resources.

Qualitative scenario development

Description

To analytically assess the potential effects, over a ten-year period, on the economy and business environment, of AI and climate change impacts, we made a range of assumptions about the magnitude and direction of those effects. Uncertainty was inherent, given complex interactions between these assumptions and other social, economic, political, technological and environmental dynamics. Our modelling was designed not to produce a singular prediction, but rather a range of calibrated outputs, each corresponding to a distinct set of input assumptions, which in planning and modelling methodologies typically are referred to as scenarios.

The scenario development began as qualitative descriptions of multiple plausible futures for how the world and economy might evolve. Each scenario featured a variety of correlated and logically consistent assumptions related to AI, the effects of climate change, and the relevant social and political dynamics that could influence their development. The qualitative narratives were converted into quantitative inputs for the economic model, with each scenario leading to a unique set of outputs. Wherever possible, we based these assumptions on peer-reviewed academic studies, or analogous historical data, choosing the high, medium or low end of the range, depending on what was consistent with the qualitative nature of each scenario.

Research method

The qualitative scenarios were developed primarily through a series of workshops led by a scenario planning expert, with contributions from subject matter experts from both inside and outside PwC. We began with a basic framework involving a few critical uncertainties, using open-ended exercises such as 'headlines from the future' to identify plausible events and stretch our thinking about what might happen under each scenario. Discussions with subject matter experts in geopolitics, economics and technology tested the logic of the scenarios, ensuring that the sequence of events was plausible within the time frame.

Several topics were explored to detail each scenario: changes in social values, agendas and consumption behaviour; the relationship between government and companies, and implied political systems; fiscal conditions and capital markets; human rights and protections; regulatory emphasis; workforce shifts; and the risk and nature of conflicts. Finally, we explored implications of these broader shifts for AI deployment and environmental solutions, which informed an 'end state' by 2035. These implications were translated into inputs for the master economic model (detailed in Section 7, on page 25).

Data

Inputs

To develop the scenarios, we used a combination of qualitative and quantitative inputs, including secondary research and discussion-based discovery. This included:

- **PwC-identified megatrends:** climate change, technological disruption, demographic shifts, fracturing world and social instability
- Articles and reports on AI adoption and regulation
- Articles and reports on environmental impacts
- Perspectives from subject matter experts in workshops
- Secondary research on early indicators of change: localised events that may signal and exemplify similar larger, global shifts that may plausibly emerge in the future.

Outputs

The process above resulted in three distinct scenarios:

- **In Trust-Based Transformation,** a coordinated, conscientious approach to tech deployment and climate response fosters productivity growth, job creation and environmental health.
- **In Tense Transition,** regionalisation and nationalism give rise to technology systems and sustainability efforts that deliver benefits without the economies of global scale.
- **In Turbulent Times,** atomised interests, divisive uses of technology, and suspended sustainability initiatives hamper economic growth.

Limitations

Scenario planning offers a structured way to consider a range of potential futures rather than definitive, singular forecasts. Some organisations might find it hard to plan and allocate across multiple possibilities.

As with any scenario exercise, not every issue or question relevant to every organisation may be covered in a single scenario. The main question for this exercise focused on the effects of AI and climate change, with an emphasis on arriving at a limited number of plausible assumptions for the quantitative model. Other issues relevant to particular domains (see Section 8, on page 31) may be less represented in these initial scenarios or may require additional work to address them at a more specific organisational level.

Baseline growth

Description

To project the potential impacts of climate change and AI on economic growth by 2035, we first needed to create a baseline growth estimate. This baseline assumed a 'business-as-usual' scenario where historical economic trends continue without significant deviations. This baseline was the foundation for additional assessment of physical climate risk under any scenario (detailed in Section 3, on page 9). The climate-adjusted baseline became the starting point for scenario-based modelling of the impact that AI adoption and decarbonisation initiatives might have on baseline growth.

Research method

Baseline growth was benchmarked against the second Shared Socioeconomic Pathway (SSP2) GDP predictions between 2023 and 2035 and was the same across all scenarios. The SSP2 'Middle of the Road' scenario assumes moderate progress in economic, population and technological areas, without significant external shocks or policy interventions.

SSP2 assumes gradual technological progress, which will include advancements in AI. To avoid duplicating AI's impact, we applied a discounted effect of AI on the SSP2 'baseline' growth. Specifically, we adjusted the baseline GDP growth figures by applying an 80% scaling factor across all countries and regions. This corresponds to a 20% reduction in baseline growth, accounting for the AI-driven component of development already embedded in SSP2's assumptions. This ensures that AI gains modelled explicitly after the baseline growth do not overlap with the implicit assumption of gradual AI-driven progress already embedded in the SSP2 trajectory.

Data

Inputs

Population and GDP numbers for baseline growth were retrieved from the SSP Scenario Explorer 3.1.0 Release July 2024 (**International Institute for Applied Systems Analysis**).

Outputs

SSP2 'baseline' growth with a discounted effect of AI.

Limitations

SSP2 assumes the world develops at a moderate pace, without major disruptions and based on historical growth trends. This reliance on SSP2 introduces the assumption that past trends are a reasonable guide to baseline future economic growth, which may not fully capture the 'baseline' scenario globally through to 2035. However, using SSP2 ensures consistency across scenarios and aligns with widely used scenario frameworks.

The contribution of technological advances to GDP growth varies across countries and time periods. The 20% growth adjustment (intended to avoid double-counting AI benefits embedded in SSP2) is an estimate based upon literature (Manyika & Roxburgh, 2011). This assumption carries risk, as the precise proportion of AI-driven growth within SSP2 is not defined and may vary across regions and countries. However, since this adjustment is applied only to the baseline, and all modelling scenarios build upon this foundation, any potential misestimation does not impact the relative differences between scenarios.

Physical climate risk adjustment

Description

The economic impact of physical climate risk is a new variable not captured by most conventional general equilibrium models, including PwC's. To begin capturing potential impacts, PwC climate risk modelling experts sought to project the threats that physical climate risks might pose to specific activities and assets under different emissions scenarios. Because these 'micro' assessments proved difficult to meaningfully integrate, on a global level, with our overall modelling approach, we instead built into our economic model new, external academic climate research indicating that unavoidable physical risks could significantly reduce GDP growth in the near term. This integration enabled a downwards adjustment to baseline GDP growth to 2035 to account for the impact of physical climate risk.

Research method

PwC climate risk modelling experts estimated the physical risks of climate change at year 2035 under two widely used, scientifically vetted physical climate scenarios: a low-emissions scenario (SSP1-2.6) and a high-emissions scenario (SSP5-8.5), both developed by the Intergovernmental Panel on Climate Change for its Sixth Assessment Report. PwC's climate scientists ran both scenarios through climate models—physics-based computer simulations of Earth's climate—under the Coupled Model Intercomparison Project (CMIP) to produce estimates of physical risks, which is a standard approach for this sort of climate risk modelling. Although these analyses yielded rich descriptive results at a quite granular level, when we sought to integrate two core economic drivers (usable cropland and labour productivity) into our macroeconomic model, we found that there was little to no difference across various emissions scenarios and that the economic transmission mechanisms at our disposal were too limited to yield meaningful results.

In light of these results, we sought to augment our research with external academic research that could create a common, climate-adjusted baseline growth figure to serve as a foundation for assessing the potential impact of three scenarios for the size and growth of economies between now and 2035. Each scenario started with a common, climate-adjusted baseline growth figure, reflecting the findings of our PwC climate risk modelling experts that during the decade ahead, the macroeconomic impact of physical climate risk will be virtually identical across various emissions pathways.

The starting point was baseline growth figures derived from the SSP2 projections, which we adjusted to account for physical climate risk. Adjustment is non-trivial due to the uncertainty of climate impacts over the next few decades. Leading academics have attempted to model this impact. We used a recent paper, ‘The economic commitment of climate change’ (Kotz et al., 2024), published in Nature—a leading peer-reviewed journal—whose findings have also been integrated in the forward-looking scenarios of the Network for Greening the Financial System (NGFS), a consortium of more than 100 central banks and financial supervisors.

Kotz et al. (2024) argue that the persistence of climate impacts on economic growth rates is a key determinant of the magnitude of damages. From their published results, we’ve applied the average climate physical risk impact in 2035. Because this value is highly uncertain, the authors provide a confidence interval. The 90% confidence interval suggests that the impact on global income per capita in 2035 could be between –3.6% and –15.5%. Our estimate of climate physical risk is –6.8% of GDP at the global level, which is well within the confidence intervals stated in Kotz et al. (2024). Given the uncertainty of climate impacts in both the academic literature and reality, we posit that our climate physical risk figure is directionally correct and within the expected range. We may elect to revise these figures as new data becomes available.

Data

Inputs

Initial inputs: PwC climate-risk modelling experts used a diverse range of sources. To illustrate, for the arable land cropland analysis:

- Input data to the aridity index was from four ISIMIP3b downscaled climate models (Hempel et al., 2013). We used the IPSL-CM6A-LR, MPI-ESM1-2-HR, MRI-ESM2-0 and UKESM1-0-LL models for SSP1-2.6 and SSP5-8.5. Following prior work (e.g., Middleton & Thomas, 1997; Huang et al., 2016; Park et al., 2018) we used annual total precipitation and annual total potential evapotranspiration to create an annual aridity index. Potential evapotranspiration was computed following the Hargreaves (1994) method, which uses daily minimum and daily maximum temperature as an input.
- Input data for the drought model was from five ISIMIP3b downscaled climate models (Hempel et al., 2013). We used the GFDL-ESM4, IPSL-CM6A-LR, MPI-ESM1-2-HR, MRI-ESM2-0 and UKESM1-0-LL models for SSP1-2.6 and SSP5-8.5. Monthly precipitation and potential evapotranspiration were used from the models for drought assessment.

Final inputs: All data are from the Kotz et al. (2024) analysis.

Outputs

Adjusted baseline GDP growth by 2035.

Limitations

See above for the challenges associated with aggregating micro-climate risk assessments into macroeconomic impacts. Additionally, the Potsdam Institute for Climate Impact Research, in Germany, provides raw data on country-specific impacts only for 2049 and a global time profile from 2021 to 2049. Since no country-specific or regional time profiles are available, we apply the global time trend to all countries. For example, if the global time profile states that 40% of 2049 impacts will be realised by 2035, we assume that each country's impacts also follow this trend. This approach assumes uniformity in how countries reach their 2049 impacts, which may not fully capture regional/country-specific differences in impact time lines. However, without access to country-specific or regional time profiles, this assumption ensures alignment with the published raw data and avoids introducing additional, less defensible assumptions.

Additionally, our model is centred on 2023 GDP values, whereas the Potsdam Institute's data uses a 2021 baseline. To align the impacts with true reported GDP growth, we adjusted the Kotz et al. (2024) estimates to reflect the fact that part of the climate impact has already occurred by 2023. This adjustment introduces an assumption that the impacts modelled by the Potsdam Institute for 2021–23 have materialised. However, this rebasing ensures consistency with our baseline model and aligns impacts with the most accurate GDP data available, making it robust and transparent.

The reliability of data and methodology presented in this paper is still under review. Should material revisions be made to the data outputs, we will endeavour to update our models accordingly.

AI model

Description

The AI model aims to project the economic impact and opportunity presented by AI adoption and the deployment of AI solutions. The model presents three different views of the world through varying levels of Responsible AI deployment. This is the second input to the master economic model (detailed in Section 7, on page 25).

Research method

We used a system dynamics model in which nodes (such as 'AI investment' and 'external communications') are linked to one another in either a positive (e.g., as one changes in one direction, the other changes in the same direction) or a negative (e.g., as one changes in one direction, the other changes in the other direction) relationship. A system dynamics model is a computational approach used to understand the behaviour of complex systems over time. It utilises stocks, flows, feedback loops and time delays to represent the interconnections and interactions among system components. System dynamics models are particularly effective in capturing nonlinear behaviours and identifying potential points of intervention within a system. The model focused on an individual company, which may exhibit different behaviours in its AI implementation: responsible, typical or reckless. The mix of companies in the world (with more reckless than responsible in the Turbulent Times scenario and the reverse in the Trust-Based Transformation scenario) was determined, simulated and aggregated into an entire ecosystem. To qualitatively assess the magnitude of impact within these relationships, we employed 'T-shirt sizing' (extra small, small, medium, large, extra large) as a heuristic tool. The size of the 'T-shirt' is indicative of the size of the effect or link between nodes—each increase in size indicates doubling of the size of the effect. For example, small is twice the impact of the effect of extra small, medium is twice the impact of the effect of small, and so on.

Data

Inputs

- **AI budget:** size of the budget a company dedicates to AI products and services (in US$).
- **AI companies:** number of companies focused on developing AI products and services.
- **AI incident impact:** severity of the impact of an AI incident.
- **AI incidents:** number of public AI incidents.
- **AI investments:** total investment value in AI (in US$).
- **AI jobs:** jobs in AI as a percentage of total job postings.
- **AI market size:** total addressable market for AI (in US$).
- **AI trust:** level of external (public) trust in a company's AI products and services, indexed 0–100.
- **Government regulation of AI:** level and efficacy of government regulations related to AI, indexed 0–100. These were modified depending on which scenario was being run. Our Trust-Based Transformation scenario increased the index slightly, and the Turbulent Times scenario decreased the index slightly.
- **Responsible AI budget:** size of the budget a company dedicates to Responsible AI (in US$).
- **Task replacement:** percentage of tasks within a business that can be automated using AI.

Outputs

- **AI adoption:** AI adoption was estimated by showing the change in AI adoption from the base year to 2035, broken down by region, sector and scenario. It represents the degree of 'meaningful' adoption of AI technologies, beyond the generally available AI embedded in nearly all devices and applications today and in the future (e.g., autocorrect).
- **Net task change:** the integration of AI is expected to reshape productivity with key improvements in automating routine tasks, enhancing decision-making and optimising operations. Although gains can drive economic growth, there's a risk of exacerbating inequality—this is especially true in the Tense Transition scenario, which emphasises national/regional interests.

Limitations

- As with any model, not all aspects of reality can be captured, which means that compromises are inevitably made.
- Modelling of individual companies was concentrated primarily on their decisions about AI, and took less into account the industry they were in and the products or services they created or delivered.
- Companies did not interact directly with other companies; therefore, synergies and competition were not captured directly.
- The projected distribution of attitudes of companies (i.e., how many companies act recklessly in relation to AI, and how many act responsibly?) was estimated and not based on projected data. This estimate was based on discussions with subject matter experts in Responsible AI and AI strategy at PwC. Generally, it was assumed that in the Trust-Based Transformation scenario, about two-thirds of the companies would have fully responsible practices, but in the Turbulent Times scenario, about two-thirds of the companies would not have any responsible practices (besides the bare minimum needed for legal compliance).

Climate transition risk model

Description

The NGFS climate-transition risk model projects out the risks incurred by transitioning to a net zero economy. The model uses the Net Zero (low emissions) and Current Policies (high emissions) NGFS scenarios, as well as Fragmented World (a blended scenario), to model three future views of the world. These represent the third input to the master economic model (detailed in Section 7, on page 25).

Research method

We used a global integrated assessment model. The Global Change Analysis Model (GCAM) is an integrated, multi-sector model. The role of models like GCAM is to bring multiple human and physical Earth systems together in one place to shed light on system interactions. GCAM allows users to explore what-if scenarios, quantifying the implications of possible future conditions. These outputs are not predictions; they are a way of analysing the potential impacts of different assumptions about future conditions.

The model applied a 1.5°C pathway (Trust-Based Transformation), a 2.5°C pathway (Turbulent Times) and a mixture of a 1.5°C pathway in some and a 2.5°C pathway in other regions (Tense Transition) along market-standard transition scenarios (Richters et al., 2024; International Energy Agency, 2023).

The goal was to gain insights into the impacts of different climate transition pathways on the global and regional energy systems and economies.

Scenario	Trust-Based Transformation	Tense Transition	Turbulent Times
Description	The model depicts this scenario as a high-ambition scenario for climate change mitigation, enabling a trajectory that supports the curbing of global warming to 1.5°C.	The model assumes a divergent, region-specific development, where some regions/countries follow a 1.5°C pathway and others a 2.5°C pathway.	The model depicts this scenario as a business-as-usual scenario for climate change mitigation, along current transition dynamics, resulting in global warming of 2.5°C.
Approach	Within this model, all values derive either directly or via calculation from 1.5°C values of the transition scenarios used (primarily Net Zero 2050 by the NGFS; Richters et al., 2024).	For this model, either the 1.5°C or 2.5°C pathway was applied at a regional level. This was done by mapping the emissions pathways of the Fragmented World scenario of the different regions to those of the Net Zero 2050 and Current Policies scenarios. Then, the existing results of the other two models were assumed for the regions depending on their mapping.	Within this model, all values derive either directly or via calculation from 2.5°C values of the transition scenarios used (primarily Current Policies by the NGFS; Richters et al., 2024).
Assumptions	All developments follow a 1.5°C pathway.	Developments differ regionally in their climate ambition.	All developments follow a 2.5°C pathway.

For the Tense Transition scenario, we split the regions in accordance with the Fragmented World scenario. The regional mapping is based on the development after 2030 in the Fragmented World scenario. A region was mapped as a whole. Regions following Current Policies trajectory: Asia-Pacific, Africa, Latin America, Middle East, Central and Eastern Europe. Regions following Net Zero trajectory: Western Europe, North America. The intent was to simulate fragmentation, not to forecast outcomes.

Countries are classified by their trajectory in the Fragmented World scenario after 2030. The mapping is based on the emissions trajectory of the country in the Fragmented World scenario after 2030. Countries following the Current Policies trajectory: China, India, Brazil. Countries following the Net Zero trajectory: Germany, Japan, UK, US.

Portfolio decarbonisation poses financial, political and social risks, such as energy and financial insecurity, stranded assets and economic decline. Many organisations will face the challenge of managing declining asset values during the transition to a low-carbon economy. For other companies, the transition can offer great opportunities, depending on their product and service portfolios.

Transition risks

Climate transition risks arise from changes in economic activities due to climate change mitigation. Where sectors or the economy are insufficiently prepared, the changes pose the risk of decreasing profitability (i.e., lower sales, higher costs)—for example, if prior assets cannot be used in their planned capacity and thus must be depreciated, or if sales drop or investment costs increase.

Scenario description

Within the NGFS scenarios of 1.5° (high transition risk) and 2.5° (low transition risk), economic welfare development is continued into the future based on the current trajectory. Emissions are constrained to the specified warming limits, with economic activity levels shifting accordingly between activities (e.g., a strong decrease of fossil fuel usage and increase in renewable energy usage in the 1.5°

scenario). Within those constraints, supply and demand determine prices on a year-to-year basis, assuming no foresight, i.e., not optimising the transition costs of the whole economy over time.

Calculation approach

- **Carbon intensity and energy efficiency:** we aggregated diverse subsectors (e.g., steel, cement, chemicals and non-ferrous metals) to broader sector categories like manufacturing. Energy consumption and emissions were normalised by the economic output (sales).
- **Stranded assets:** we calculated how much investment was lost if the sectoral activity was aligned with the necessary pathway (i.e., the production levels of manufacturing and the loss of real estate surpassing the energy efficiency threshold), accounting for prior depreciation that occurred anyway.

Data

Inputs

Data was retrieved from NGFS Phase IV (Richters et al., 2024), except for 'Levelised cost of electricity,' which was retrieved from the International Energy Agency (2023).

- **Agriculture:** activity of the agricultural sector in the form of the effective harvest (without moisture content).
- **Capital investment costs (steel, real estate, electricity generation):** investment in assets (in US$).
- **Cement production:** tons of cement produced.
- **Chemicals production:** tons of chemicals (e.g., high-value chemicals and ammonium) produced.
- **Electricity generation by source:** electricity produced per year and source, expressed in exajoules (10^18 joules).
- **Energy consumption:** energy consumed during the year.
- **Fossil fuel production and trade:** levels of fossil fuel production and trade (with other countries), expressed in exajoules (10^18 joules).

- **Kyoto gases emissions:** sum of greenhouse gases emitted, expressed in CO_2 equivalents.
- **Levelised cost of electricity:** cost of electricity production over the technology's lifetime.
- **Maritime activity:** transport activity level in maritime subsector, measured in tonne-kilometres (product of load and distance travelled).
- **Non-ferrous metal production:** tons of aluminium produced.
- **Rail, aviation, road activity:** transport activity levels for these subsectors, measured in vehicle kilometres (distance travelled, irrespective of load).
- **Real estate:** area of real estate in square metres.
- **Sales per sector and country:** economic expression of sector activity, measured by the value of its sales per country.
- **Steel production:** tons of steel produced.

Outputs

- **Energy efficiency:** percentage change in efficiency relative to the base year (2022).
- **Stranded assets:** percentage change of capital that becomes stranded (no longer in use) due to technological shifts fuelled by climate change.
- **Renewable energy ratio:** percentage of energy consumption from renewable sources relative to total energy consumption in a given year.

Limitations

GDP growth rates vary depending on climate scenario and territory/region; therefore, activities that are used for intensities calculation are impacted by GDP developments. To mitigate this, we standardised GDP assumptions across all models. Further, when estimating the stranded asset effect, mining and electric utilities consider production losses; assets are also needed for production, creating the potential for an overlap in effect. If activity data was not available for energy/emission intensities, sales (in US$) were used as a proxy for intensities. The price of electricity was available only for major regions; other regions and countries were approximated using their electricity mix.

06

Climate–AI interaction model (CLAIM)

Description

The CLAIM model captures the interaction between climate and AI. The model assesses the impact of AI adoption on energy consumption and energy efficiency (e.g., through increased data centre use). The outputs from this model were not used directly in the master economic model. Instead, we used the outputs of this model (1) as an independent check on the effect of climate and AI in the master economic model, and (2) to investigate the circumstances under which AI-driven energy efficiencies would offset AI-driven energy output. To do this, the outputs from the climate transition risk model were adjusted by the CLAIM model.

Research method

The CLAIM model is a system dynamics model that simulates the effects of AI adoption on energy use and emissions under the scenarios. It is designed to capture dynamic interactions in the climate–AI relationship. There are complex relationships and feedback loops between different variables in the CLAIM model, including AI adoption, energy consumption, emissions, water availability, and other related factors. We employed 'T-shirt sizing' (small, medium, large) as a heuristic tool for magnitude of impact, as in the AI model (see Section 4, on page 13).

Based on discussions with subject matter experts, we assumed that for every percentage point increase in the share of business activity that is enabled by AI, there is a 0.4 percentage point increase in the energy efficiency of data centres. Outside of data centres, we assumed that for every percentage point increase in the share of business activity that is enabled by AI adoption, there is also a 0.1 percentage point increase in energy efficiency. For example, if the share of business activity enabled by AI increases from 12% to 32% over ten years, the 20 percentage point increase translates into a 2% increase in energy efficiency outside of data centres.

The higher rate for efficiency in data centres is based on the expectation that as companies increase their investments in AI, they will seek to reduce energy consumption and operational costs more aggressively in energy-intensive environments like data centres. As a result, data centres are expected to improve their energy efficiency at approximately four times the rate of non–data centre sectors. This assumption is supported by research and real-world advances. For example, limiting the amount of power that a graphics processing unit can consume, a practice known as power capping, can reduce the energy needed to train a transformer-based language model by 15% (McDonald et al., 2022).

Data

Inputs

- **Data centre local areas:** the number of data centres mapped to each local area. A local area is geographically defined by a pocket of data centres in one location.
- **Emissions:** amount of emissions emitted by sector and region each year.
- **Energy efficiencies for data centres:** percentage change in efficiency with base year (2022).
- **GCI drought risk scores:** based on the frequency and severity of drought, with higher risk scores indicating higher levels of risk.
- **Split of energy consumption for data centres vs. non–data centres:** global energy use split between data centres and non–data centres. Data centre energy use is subtracted from the global energy use to get the value for non–data centres.

- **Water availability (for data centres):** the amount of blue water that is available per year after it has been used upstream e.g., by houses and drinking water).
- **Water consumption:** the amount of water consumed by data centres per year.

Outputs

Adjusted energy efficiencies: the percentage change in efficiency compared to the base year (2022). This is a key indicator of how sectors are adopting and benefitting from energy-efficient technologies.

- **Adjusted renewable energy ratio:** percentage of energy consumption from renewable sources relative to total energy consumption in a given year. This is critical for assessing the transition to sustainable energy practices.
- **Energy consumed in data centres:** total amount of energy consumed by a data centre, expressed in exajoules (10^18 joules) per year.
- **Energy consumed outside data centres:** total amount of energy consumed outside a data centre, expressed in exajoules (10^18 joules) per year.
- **Emissions:** total amount of greenhouse gas emissions produced across the entire ecosystem, measured in terms of CO_2 equivalent, expressed in million metric tons of CO_2 equivalent per year (Mt CO_2-equivalent per year).
- **Adjusted total energy consumption:** energy consumption in both data centres and non–data centres. Encompasses all forms of energy, both renewable and non-renewable.

The CLAIM outputs were evaluated under the three scenarios. For modelling purposes, the key parameters used in these scenarios are as follows:

Scenario	AI adoption strategy	Climate transition
Trust-Based Transformation	Responsible	NGFS Net Zero 2050
Tense Transition	Typical	NGFS Fragmented World (variation)
Turbulent Times	Reckless	NGFS Current Policies

Limitations

Specific data centre water consumption is not known, so assumptions are made for small, medium and large data centres based on research (e.g., Hölzle, 2022). Data centre distribution of small, medium and large was unknown, so assumptions were made. Small data centres were about 30% of the market and liquid-cooled ones used about 20,000 litres per day. For medium data centres, these values were 50% and 300,000 per day; and for large, 20% and 1,000,000 per day. By 2035, small was assumed to be 20%, medium 50%, and large 30%. These assumptions impact how we measure water consumption for data centres. However, we found projections that display the growth of large data centres for AI and these use the most water, limiting our margin of error. Energy consumption, efficiencies and water consumption are all expected to be sector agnostic, so we did not adjust them by sector. Further, we used AI adoption as the proxy for AI growth.

The CLAIM model was calibrated to the datasets for energy consumption, energy efficiency and green energy share. Data for some climate-relevant variables, such as emissions and drought risk, was not used in the calibration, although these variables and their relevant mechanisms were included in the CLAIM model. The CLAIM model depends on the accurate linkage between the baseline AI adoption data and the corresponding climate-related datasets provided by the AI team. Such accurate linkage is affected by the assumptions made and the error potentially introduced when generating the datasets. Therefore, the accuracy of predictions of the CLAIM model depends on the underlying assumptions and datasets supplied.

Master economic modelling

Description

The master economic model combined the efforts from all the other models, except for the CLAIM model, to project the impact of AI and climate on various macroeconomic metrics. The model generated outputs for three future scenarios by using the metrics produced for the respective scenarios by the upstream modelling efforts.

Research method

We conducted a computable general equilibrium (CGE) analysis to explore economic outcomes based on six inputs shaping the global landscape, amid the integration of AI and the evolving challenges of climate change. More precisely, a standard global trade analysis project (GTAP) model (Corong, 2017) was used to analyse the economic impacts of different inputs. It incorporated data from various countries and sectors, and simulated the interactions between global markets, production, and consumption. The model is widely used to assess the effects of trade liberalisation, climate policies, and emerging technologies by examining how changes in one part of the economy—such as tariff adjustments or carbon pricing changes—affect prices, production, consumption and welfare across multiple countries and sectors.

To explore how the world might respond differently to these developments, we modelled three different scenarios: Trust-Based Transformation, characterised by global cooperation and responsible innovation; Tense Transition, focused on national/regional priorities and fragmented AI adoption; and Turbulent Times, marked by rapid, poorly governed technological advances leading to social and environmental issues. Each scenario was characterised by a unique set of inputs, resulting in three distinct economic futures. This exploration aims to illuminate how diverse uses of AI and diverse responses to climate challenges can shape global economic outcomes.

We assumed population trends to be the same across all scenarios. This only impacted baseline numbers and has no effect on model outputs across different scenarios.

Data

Inputs

The master model leverages outputs from the AI and climate transition risk models to project various macroeconomic metrics across three different futures, each of which started with the same assumption about baseline growth, adjusted for physical climate risk as described above.

1. **Baseline growth**
   - Adjusted baseline growth

2. **AI effects**
   - AI adoption
   - Net task change

3. **Climate transition risk effects**
   - Energy efficiency
   - Stranded assets
   - Sustainable mix

AI inputs

- **AI adoption:** the change in productivity based on the number of firms integrating AI in a given year. AI adoption coefficients are based on research by Czarnitzki et al. (2023) on firm-level productivity and AI along with extended literature review on the economic implications of AI adoption.
- **Net task change:** a labour share shock based on net amount of tasks that move from labour to capital as a result of AI. Task creation coefficients are informed by the existing literature, which explores the dual impacts of automation on labour markets. Research indicates that automation can lead to task destruction by eliminating routine and repetitive tasks, particularly those that can be codified into algorithms or performed by machines (Autor, 2024; Bessen, 2020). However, automation can also drive task creation by generating new types of work, often requiring human oversight, problem-solving, creativity or interaction with emerging technologies.

A different figure was modelled for each depending on the scenario:

Trust-Based Transformation

Democratisation and responsible use of technology translates into sizeable productivity gains from AI adoption. In this scenario, we assume the productivity elasticity for AI adoption to be high. Moreover, tasks previously performed by human labour that have been replaced by AI are offset by the creation of new tasks. This results in a net task increase.

- **AI adoption productivity elasticity:** 0.33 (adopting AI increases productivity by 33%).
- **Net task creation of replaced tasks:** 1.2 (for every ten human tasks automated by AI, 12 new human tasks will be created).

Tense Transition

In a more cautious world, prioritisation of national/regional stability and local optimisation of socioeconomic consequences leads to more limited gains from AI.

In this scenario, we assume productivity elasticity for AI adoption to be more moderate. All tasks shifting from human labour to capital due to AI are offset by new tasks created.

- **AI adoption productivity elasticity:** 0.17 (adopting AI increases productivity by 17%).
- **Net task creation of replaced tasks:** 1.0 (for every ten human tasks automated by AI, ten new human tasks will be created).

Turbulent Times

AI is used irresponsibly. An overemphasised short-term view and the absence of guardrails yield disappointment and AI events that collectively harm business trust in the fundamental rewiring of organisational functions and tasks, limiting productivity gains from AI. In this scenario, the productivity elasticity for AI adoption is small. Moreover, task creation is less than the proportion of tasks being replaced by AI.

- **AI adoption productivity elasticity:** 0.01 (adopting AI increases productivity by 1%).
- **Net task creation of replaced tasks:** 0.8 (for every ten human tasks automated by AI, only eight new human tasks will be created).

Climate inputs

- Energy efficiency
- Stranded assets
- Renewable energy ratio

A different figure was modelled for each depending on the scenario; see Section 5 for detail on scenario-specific assumptions.

Outputs

- **GDP:** Measure of the total dollar value of goods and services produced within a country’s borders (in US$, 2022 inflation adjusted), serving as an

indicator of economic health and allowing for comparisons between nations. Produced at a region and country level. Unit of measure: US$ billions or % growth relative to 2023.
- **GVA:** Measure of the total dollar value of goods and services produced by different sectors of the economy, such as agriculture, manufacturing and financial services (in US$, 2022 inflation adjusted), providing insights into the contribution of each sector to overall economic output. Unit of measure: US$ billions or % growth relative to 2023.

The outputs generated were produced at the following levels:

- **Global GDP:** aggregation of regional/national GDP results.
- **Geographic GDP** (region-level results for Africa, Asia-Pacific, Central and Eastern Europe, Latin America, Middle East, North America and Western Europe).
  - National GDP (country-level results for Brazil, China, Germany, India, Japan, UK and US).
  - Sector-level GVA (17 sectors, as defined by Standard Industrial Classification codes, including key economic areas such as manufacturing, professional services, agriculture and IT).

Limitations

One of the key limitations of any CGE model is its reliance on input–output (I–O), which represents the interconnections between industries, trade flows and national economies. The GTAP database is updated periodically, but national I–O tables often have significant time lags. Some country datasets may be several years old, leading to mismatches between the real economy and the modelled economy.

Additionally, CGE models depend heavily on elasticity parameters, which determine how consumers and producers make substitutions between domestic and foreign goods, how labour and capital respond to shocks and how trade flows adjust to policy changes. However, these elasticities are often estimated from past studies or generalised from a few available datasets, rather than being derived from real-time or country-specific data. This can lead to biased or overly simplified results, particularly when they are applied to sectors or regions where trade patterns are rapidly evolving.

Finally, CGE models struggle to capture structural breaks caused by sudden, nonlinear changes such as economic crises, geopolitical shocks or climate tipping points. For example, a climate-induced food crisis could trigger inflation, trade disruptions and migration, effects that equilibrium-based CGE models fail to predict. Since these models assume smooth adjustments over time, they fail to accommodate rapid or nonlinear structural breaks.

Sector–domain mapping

Description

Sectors were allocated to six domains of growth and three enabling domains (see the ISIC Sector table in this section) using input–output tables. This allocation allowed GVA output from the master economic model to be represented in terms of domains.

Research method

We used input–output tables to apportion sector values into domains. We aggregated the domestic and import values, as well as the sector roll-ups for the International Standard Industrial Classification of All Economic Activities (ISIC) sectors M and N and R, S, T and U. All our tables use the 2019 version of the ISIC tables. The 2020 tables are available, but carry distortions due to the impact of covid-19 that year. More recent tables are available for selected territories, though they are inconsistent in terms of formatting, currency denomination, assumptions and sector hierarchy convention (ISIC r4. vs. North American Industry Classification System [NAICS] and others).

The tables are used for the seven priority countries (Brazil, China, Germany, India, Japan, UK, US). Regional tables assumed a representative country, as shown in the table on the next page:

Region	Representative country
Africa	South Africa
Asia-Pacific	China
Central and Eastern Europe	Poland
Latin America	Brazil
Middle East	Saudi Arabia
North America	US
Western Europe	Germany

We made assumptions as to which domain each sector most strongly aligns with. We assign each sector to its most appropriate domain below. As a result, each domain has at least one 'anchor tenant,' which is the sector (or sectors) that most strongly represents the domain. This list of assumptions is below.

ISIC code	ISIC sector	Domain
A	Agriculture, forestry and fishing	Feed
B	Mining and quarrying	Fuel and Power
C	Manufacturing	Make
D	Electricity, gas, steam and air conditioning supply	Fuel and Power
E	Water supply; sewerage, waste management and remediation activities	Govern and Serve (enabler)
F	Construction	Build
G	Wholesale and retail trade	None
H	Transportation and storage	Move
I	Accommodation and food service activities	Feed
J	Information and communication	Connect and Compute (enabler)
K	Financial and insurance activities	Fund and Insure (enabler)
L	Real estate activities	Fund and Insure (enabler)
MN	Professional, scientific and technical activities; administrative and support service activities	None
O	Public administration and defence; compulsory social security	Govern and Serve (enabler)
P	Education	Govern and Serve (enabler)
Q	Human health and social work activities	Care
RSTU	Arts, entertainment and recreation; other service activities; activities of households as employers; undifferentiated goods- and services-producing activities of households for own use; activities of extraterritorial organisations and bodies	None

By assigning anchor tenants, we allocated some proportion of the total value of the sector output to that domain and let the logic of the I–O table quantitatively allocate the rest of the sector's value across the other domains, based on the relationship between the anchor tenant and each sector comprising the other domains.

The anchor tenant (AT) values are apportioned to their relevant domain in terms of their value by:

$$\mathbf{AT} = \frac{\textbf{total sector output}}{\textbf{(total sector input to other sectors + total sector output)}}$$

With the AT apportioned to its domain, we allow for the rest of the value (1–AT) to be apportioned across the other domains as per their relationship; that is, informed by the relevant I–O table, to the other sectors, which act as anchor tenants in their own right. The remaining allocation of the AT is scaled across the other domains, and scaled such that the row total of all sectors across all domains, including the 'Other' domain—a catchall domain for GVA not explicitly accounted for in the nine named domains—captures the full value of the sector output. Hence, the row total of the sector across all domains is equal to the full value (in GVA terms) accounted for.

The output is such that we are left with a matrix with sectors as rows, columns as domains and cell values of the ratio of the sector's output.

Using the outputs of the master economic model in conjunction with the above apportionments, we are then able to size both sectoral- and domain-level values in each year, for each level of additive effects of baseline growth levels, climate-adjusted baselines, AI impacts and asset stranding due to decarbonisation efforts.

This is done independently for each priority territory, as well as region, with resulting data tables that inform the bulk of the various research artefacts.

Data

Inputs

- The full set of harmonised domestic and import I–O tables are pulled from the **OECD database**.
- Outputs from the master economic modelling process.

Outputs

Values for each of the six domains of human need (How we make, How we build, How we feed ourselves, How we care for ourselves, How we move, How we fuel and power) and three enabling domains (How we govern and serve, How we fund and insure, How we connect and compute), in each year, for each level of modelling results in line with those of the master economic modelling outputs, for each geography of interest. Global figures are roll-ups of the various regional outputs.

Limitations

I–O tables are not available at the regional level, except for the EU (which does not correspond to any of the regions used in the analysis and does not use ISIC sectors). It is not possible to generate an I–O table for the other regions. We use a representative country's I–O table as a base for the regional GVA values. This has the potential to be misleading because it represents country dynamics as regional.

I–O tables show historic interdependencies. This says nothing about industry convergence, however, and nothing about how interdependencies might evolve.

Sector interdependencies can be misleading. For example, a large portion of agriculture's output goes into manufacturing. This isn't immediately logical. However, take an example of fishing output. Sardines are processed and canned (manufacturing) before going elsewhere. We do not see this 'second stage' in our methodology. A similar example could be made for the outputs of forestry, whereby logging outputs are processed via manufacturing into furniture, etc.

BMR Pressure Index

Description

The BMR Pressure Index compiles a set of leading indicators across a range of factors in order to assess the level of pressure that the average company in a given sector feels to reinvent its business model.

Our analysis tracks each year's level of pressure from 1994 to 2023 and is sector-specific.

Research method

A conceptual logic informs the factors contributing to pressure to reinvent business models. These factors, and brief accompanying conceptual logic, are:

- **Attractiveness** (firm count): increasing industry attractiveness drives new entrants and incumbents to capture emerging value. We look at the number of firms (firm count, FC) active in a given year, scaled between 0 and 1, to create the index.
- **Performance** (return on capital, return on equity): declining industry returns put pressure on companies to find ways to ensure their survival. We use return on capital (ROC) (for companies outside financial services) and return on equity (for financial services companies) as a proxy for performance, weighted by market share. Lower returns indicate higher pressure. This measure is then scaled between 0 and 1.

- **Innovation** (share of venture capital in the sector vs total venture capital share): emergence of new innovations and technologies enables companies to capture new sources of value. We use the share of venture capital (VC) in the sector vs. total VC in all sectors, scaled by the growth of VC vs. total revenue of the sector, each year. This measure is scaled between 0 and 1.
- **Shocks** (sectoral recession): shocks rapidly put pressure on companies to adapt to new conditions. Shocks are defined as years in which inflation-adjusted revenue growth contracts YoY (negative revenue growth). The larger the contraction, the higher the pressure from the shock. The measure is scaled between 0 and 1.
- **BMR occurrence** (cumulative gain of market share): the expanding adoption of new business models within an industry puts pressure on others in that industry to follow suit. The redistribution of market share between companies is an indication that BMR is occurring within a sector. Those with more successful business models win market share, while obsolescing business models lead to erosion of market share. We measured this movement of market share between companies within a sector using a three-year rolling average, recognising that the effects of BMR intensity persist as pressure into future years. The measure is scaled between 0 and 1.

Each factor is normalised, depending on the full set of available data for the factor over the period of analysis.

We define Total BMR Pressure as:

$$\textbf{BMR Pressure} = \frac{\mathbf{A}_i + \mathbf{P}_i + \mathbf{I}_i + \mathbf{S}_i + \mathbf{BMR}_{Occ}}{\mathbf{5}}$$

Data

Inputs

- Company-level financials are from Capital IQ.
- VC data is from PitchBook.

Outputs

- BMR Pressure Index values that are specific to geographic regions, inclusive of each factor's contribution in each year.
- A forecast of BMR pressure into the future (one- or two-year outlook).

Limitations

- Due to data availability, only public companies are in the sample.
- Revenue weighting can obscure the actions of small innovating companies, although incumbent companies may follow their lead.
- The maximum impact of any individual factor is set at 20% of the total pressure felt in a given year, which may understate the true pressure exerted by any individual factor.
- The regulation factor is not included in the analysis and may have an effect on pressure levels as well as overall model significance in edge cases.

BMR Value at Stake

Description

BMR value at stake (VAS) aims to quantify the revenue that changes hands within a sector–geography pairing, in a given year, as a result of business model reinvention.

Research method

From BMR Pressure Index (Section 9, on page 35), we have constructed a measure of BMR: BMR occurrence. BMR occurrence is the sum of positive market share gains for all companies in the sample of interest. Because we expect that BMR occurs between one and three years after high levels of pressure are felt, we are able to quantitatively define a relationship between BMR pressure and BMR occurrence.

Due to BMR occurrence being proxied by market share changes (which are symmetrical on the positive and negative sides), measuring the expected market share changes as a result of BMR only necessitates the isolation of the effect of BMR pressure on market share changes.

This being the case, the three components necessary for calculating the value at stake are:

- **Forecasted value of the sector:** derived from the outputs of the master economic model (climate-adjusted baseline figures in 2025).
- **Forecasted BMR pressure level (where appropriate):** employs a Prophet model with the five most recent years of pressure as significant change points to give greater weight to recent levels of pressure.
- **Isolated effect of BMR pressure on market share changes:** employs either linear or panel fixed effects regression models with the inclusion of lags.

The resulting data points allow us to simply apply the formula in order to come to the VAS figure for the sector–geography pair:

$$\textbf{VAS (US\$)} = \textbf{market shift (\%)} \times \textbf{forecasted revenue (US\$)}$$

Data

Inputs

- BMR Pressure Index
- Sector GVA from the master economic model

Outputs

- Value at stake in selected sector–geography pairs
  - In US$ terms
  - In % market share change terms

Limitations

- The relationship between BMR Pressure Index and cumulative market share gains is based on public company data. These results are applied to the full sectoral GVA figures, which include private companies. We assume the relationship is unchanged with the inclusion of private companies.
- While we isolate the effect of BMR pressure on market share changes, it is probable that we do not completely isolate this effect (by nature of the sectoral-level analysis). Thus, it is unclear whether this relationship is under- or overestimated.
- Forecasting is used throughout the various calculations made. While forecasts can extrapolate past relationships into the future, these relationships may be changing in an increasingly fast-paced, competitive, and disruption-filled operating environment.

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Value in motion: Methodology

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