Rhodium Climate Outlook: Technical Appendix

This document provides a detailed overview of the modeling framework used in the 2023 Rhodium Climate Outlook. Section 1 provides an overview of Rhodium's Global Energy Model (RHG-GEM), an integrated modeling platform that captures uncertainty in economic and population growth, oil and natural gas prices, and clean energy technology costs under likely policy evolution to provide probabilistic energy, emissions, and temperature projections through the end of the century. In Section 2, we outline the probabilistic approach to projecting energy and emissions outcomes under uncertainty, and Section 3 describes the novel approach to climate policy projections implemented in the RHG-GEM to answer the question: "what are we on track for?". Section 4 summarizes the approach used to translate GHG emission pathways from RHG-GEM into temperature outcomes, through simulations of the the Finite-amplitude Impulse Response (FaIR) model. Section 5 presents the methodology of the Monte-Carlo Analysis applied to this integrated modeling framework to capture the key uncertainties in the evolution of the energy system, future global GHG emissions pathways, and associated temperature outcomes. Finally, we describe how we project all six Kyoto gases as part of our comprehensive emissions framework.

SECTION 1: RHODIUM'S GLOBAL ENERGY MODEL

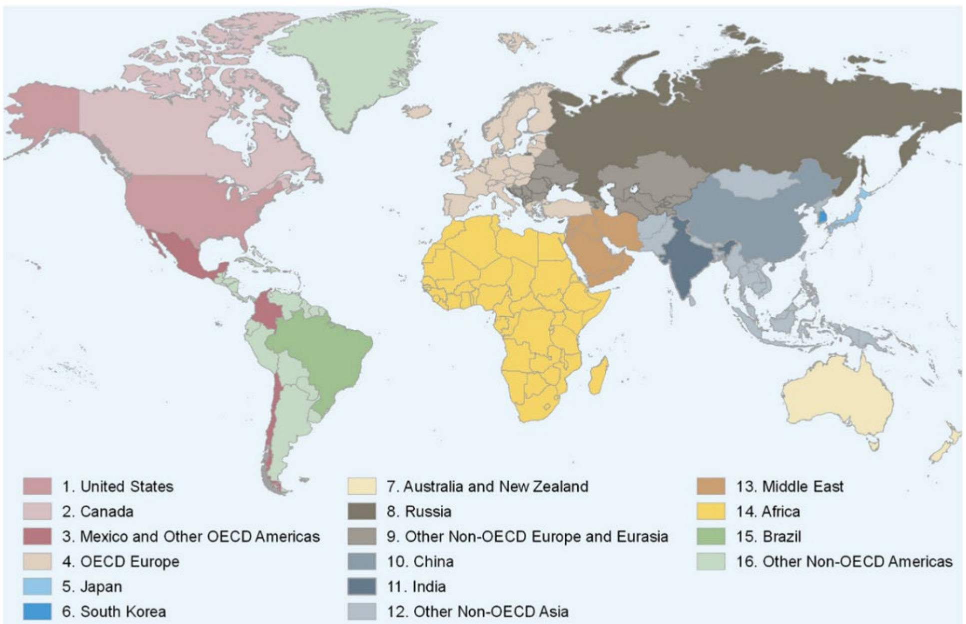
To model global energy and emissions outcomes, we use Rhodium's Global Energy Model (RHG-GEM), a highly modified version of the World Energy Modeling System (WEPS) used by the Energy Information Administration (EIA) to produce the International Energy Outlook 2021 (IEO2021). The WEPS model is designed to provide the EIA's long-term world energy projections under current policy and technology trends. As such, Rhodium invested in significantly modifying the WEPS model—and for many components overhauling the original model completely—to robustly capture a range of policy, socioeconomic, and energy market futures.

Core components of RHG-GEM

- Built for uncertainty: RHG-GEM is designed to consider a wide-range of uncertainties underpinning the energy system, including through Monte Carlo Analysis. This allows for a robust and systematic exploration of the main drivers of energy and emissions.
- Integrated platform: Our energy and emissions model is linked with the FaIR model. This allows for probabilistic temperature projections derived directly from our emissions projections that include climate system uncertainty as well.
- Clean technology characterization: RHG-GEM characterizes commercially available clean technologies, including solar, wind, utility-scale battery storage, and electric vehicles. The model integrates up-to-date technology cost and performance data and captures spatial and temporal variability of renewable energy resources. We also characterize novel clean technologies – which we collectively refer to as Emerging Clean Technologies (ECTs)—with a focus on clean hydrogen, sustainable aviation fuels (SAF), carbon capture, and direct air capture (DAC). To appropriately capture the market for clean technologies, we also characterize complementary and competitor technologies and relevant supporting infrastructure.
- Clean technology demand: In the industrial, transport, and building sectors we allow for fuel substitution and clean technology adoption based on relative costs and performance, consumer behavior, and historically-calibrated fuel-switching potential.
- Integrated supply and demand: Demand is determined endogenously in the model, based on GDP, population, energy prices, and other drivers. Demand and supply solve iteratively in the model, producing a general equilibrium solution on an annual basis.

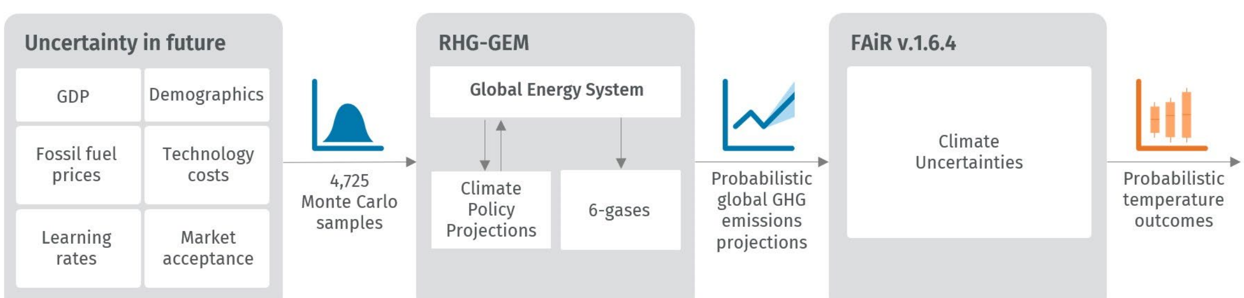
- Regional: RHG-GEM models 16 world regions that consist of countries and country groupings within the broad divide of the Organization of Economic Cooperation and Development (OECD) and non-OECD countries (Figure 1).
- Modular: RHG-GEM has a modular structure. The main modules consist of: electricity and heat, oil and gas supply, industry, transport, buildings, and non-energy emissions, along with a climate policy module. This modularity enables us to design the methodology and assumptions most suited to each sector. RHG-GEM is also designed to easily link with other models, including FaIR.
- Model timeframe: Our time horizon extends to 2100, which allows us to provide a methodologically consistent set of global emissions and temperature rise projections. And as 2050 gets closer, looking beyond mid-century provides useful insights into regional energy and sectoral emissions dynamics.

FIGURE 1
RHG-GEM regions



Source: EIA WEPS

FIGURE 2
The integrated RHG-GEM platform



Source: Rhodium Group

Energy system and emissions modeling

Electric power sector and clean technology production

Rhodium's electricity and emerging clean technology module (REEM henceforth) is built using the TIMES model framework, which uses a linear programming approach to explore cost-optimal configurations of the future energy system. The model objective is to minimize total discounted system costs. Features of this formulation include perfect competition (no market power held by specific firms) and perfect foresight (market players have all information about the present and the future, to inform investment decisions). The utilization of an optimization framework in modeling the power sector and emerging clean technology supply allows for the identification of the most efficient and economically viable pathways to meet energy demands, while explicitly diving into the complex dynamics that result from the alignment of policy targets with the inherent constraints tied to the physics of energy systems.

The REEM projects generating capacity (including additions and retirements), generation, fuel consumption, carbon dioxide (CO_2) emissions, and prices for the electric power and heat sector, hydrogen and sustainable aviation fuel production. Integrating emerging climate technologies into the REEM's least-cost optimization framework allows these technologies to compete for market share with incumbents and clean alternatives. Moreover, we are able to capture sector coupling between the electric power system and electricity-based technologies (e.g. electrolysis, power-to-liquids, and DAC).

The REEM receives electricity, district heat, hydrogen, and sustainable aviation fuel demand from each end-use sector (residential, commercial, industry, and transport), oil and gas supply curves from the oil and gas sector, along with captured CO_2 from the industrial module. For each of the end-use modules, the REEM provides the following projections:

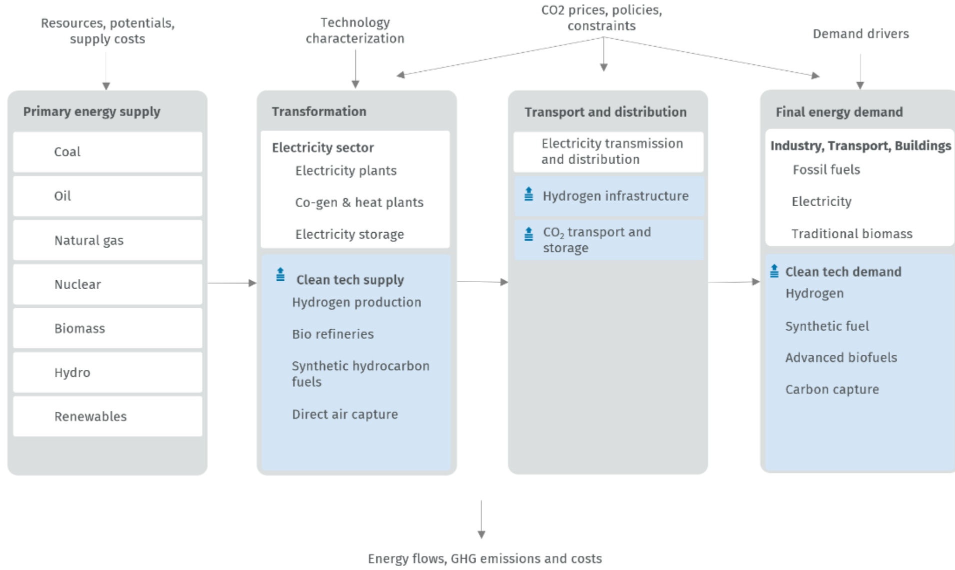
- Biomass, electricity, district heat, hydrogen, and sustainable aviation fuel wholesale prices
- Electricity retail prices
- Fuel consumption to produce electricity, hydrogen, and alternative fuels
- Carbon dioxide transport and sequestration costs

Power and heat production

The modeling of the existing power stock takes into account the installation year of each plant and is derived from data sourced from the Platts' World Electric Power Plant database. Adjustments to the database have been implemented as needed to align with the most recent data on installed capacity where available. Renewable electricity potentials, encompassing solar, wind, and hydro sources, are modeled at the country level. Hourly capacity factors for renewables can be consolidated into 12 or 36 annual time slices. This allows user-control over the number of annual time slices offering flexibility in representing seasonal and time-of-day variations in electric load and supply. For the purposes of the RCO 2023, we use 12 time slices to lower computational burden given the need to run many trials in our Monte Carlo Analysis (MCA).

The model explicitly incorporates early economic retirement and capacity retrofits. While non-economic capacity often persists in the real world due to local must-run considerations, institutional practices, and other factors, the REEM introduces decay constraints. These constraints limit the rate of decrease in coal, gas, and oil power capacity, specifying a maximum annual percentage rate of decline and a representative unit size that can be retired beyond the annual percentage rate, allowing capacity to reach zero. Residual gas and coal plants are constrained to maintain a minimum of 20% annual capacity factor each.

FIGURE 3
Overview of the REEM energy system
Clean technologies and related infrastructure are highlighted in blue.



Grid reliability is addressed through reserve capacity requirements, obligating suppliers to uphold sufficient generating capacity that exceeds peak demand by a specified margin. This constraint assigns dependability factors to each power plant type, representing the percentage of installed capacity the grid can rely on in case of outages. The reserve capacity requirements constraint applies to each region and year as follows:

$$\sum dependability_{plant\ type\ i} \times installed\ capacity_{plant\ type\ i} \geq reserve\ m\arg i\,n \times peak\ electricity\ demand$$

The dependability factors and reserve margin have been sourced through a comprehensive literature review. Dependability percentages for variable renewable sources and hydro have been established at 15% and 50%, respectively. Notably, storage devices are excluded from consideration within this constraint. Reserve margin has been set at 25%.

We consider the uncertainty in cost and performance parameters for renewable power generation technologies in the MCA, including solar, wind and utility scale batteries. Cost and performance for power generating facilities equipped with carbon capture technology are informed by Rhodium analysis and current literature. This includes work from the National Energy Technology Laboratory, which details cost and performance for natural gas-fueled direct supercritical CO_2-fired power plants.

Emerging clean technologies

Clean hydrogen: We model clean hydrogen production from electrolysis, biomass gasification, methane pyrolysis, and fossil with carbon capture, as well as unabated fossil-based hydrogen production pathways. Hydrogen demand covers both existing uses of hydrogen, including in the chemical and refining sectors, and new uses, including other industries, fuel cell vehicles, power and heat generation, and power to liquids/gas. All demands except hydrogen used for fuel production are exogenous to the IEMM and originate from other RHG-GEM modules. We assume hydrogen for existing uses can be sourced by any hydrogen pathway, with the exception of methanol and ammonia transformed into urea. In those sectors only unabated or CCS-equipped hydrogen pathways can fulfill hydrogen demand, reflecting the need for carbon in these industrial processes. In general, we assume new sources of hydrogen demand can only be produced by clean pathways.

Sustainable aviation fuels: SAF technologies modeled include Hydroprocessed Esters and Fatty Acids (HEFA), biomass gasification Fischer-Tropsch with and without CCS and power-to-liquids Fischer-Tropsch. We assume these fuels can be blended with jet fuel at any ratio to be used as "drop-in" fuels for domestic and international flights. Demand for SAF originates in the RHG-GEM transportation demand module.

Direct air capture: DAC modeling in the IEMM explicitly differentiates between the solid sorbent and liquid solvent pathways. We assume heat for the process can be produced on-site or off-site.

We establish current cost and performance figures for each ECT pathway through extensive literature reviews, expert interviews, and Rhodium analysis. The costs are a culmination of the capital costs, non-energy operation and maintenance expenses (both fixed and variable), financing rates, and energy inputs.

RHG-GEM incorporates endogenous technology learning for clean hydrogen and DAC to project future capital costs of these technologies based on a learning-by-doing approach. Capital costs are updated across model run iterations based on cumulative technology installed capacity. To address the decline in learning rates with deployment, we employ a three-tiered model for technology learning rates. The "revolution learning rate" pertains to the early stages of deployment, the "evolution learning rate" signifies a rapid deployment phase, and the "commercial learning rate" corresponds to the mature stage of technology deployment. Thresholds for each phase are established through expert judgment. The uncertainty in technological learning rates are considered in our MCA.

Hydrogen production, delivery and storage

Hydrogen capacity is derived from data developed by the Pacific Northwest National Laboratory (PNNL) that has disaggregated data for the US, Europe, China, and the rest of the world. Regional hydrogen demand is used to estimate installed capacity in the rest of the world by REEM region. Planned hydrogen plants are extracted from the IEA's 2023 hydrogen projects database and are aggregated by plant and fuel type. Hydrogen supply is possible through coal gasification without and with carbon capture, steam methane reforming (SMR henceforth) without and with carbon capture, methane pyrolysis, biomass gasification without and with carbon capture, and electrolysis. Cost and performance parameters associated with production technologies are based on Rhodium analysis for electrolysis and the IEA's future of hydrogen study for all other production technologies.

Hydrogen delivery and storage modeling are based on the Joint Research Centre's work on hydrogen supply chain architecture for bottom-up models. This includes three hydrogen storage possibilities: large scale underground storage (UGS), centralized and decentralized tank storage. The efficiency of hydrogen UGS is assumed to be similar to the current operating natural gas UGS facilities whereas the efficiency of tank storage is assumed to be around 80%. We also assume that the three storage technologies could be used as seasonal storage solutions. Delivery costs range between 7.04 $/kg and 11.38 $/kg depending on the different potential delivery pathways.

Carbon transport and storage

Carbon transport and storage costs are based on the EIA's WEPS model and are estimated to be 40$/t$CO_2$. We assume annual CO_2 injection rates that become less constraining over time as new storage resources are developed and technology improves. For Europe, we limit annual CO_2 injection rates to 300 Mt, in line with the 1.5Tech scenario of the EU Long Term Scenarios used in the European Green Deal negotiations.

Biomass supply curves

We developed biomass supply curves based on publicly available Globiom-G4M biomass supply curves from the International Institute for Applied Systems Analysis (IIASA). This data represents the regional availability of delivered bioenergy at prices ranging between 3$/GJ and 60$/GJ . To develop HEFA feedstock potentials, we identified different types of oil feedstocks that constitute potential HEFA feedstock candidates based on a technoeconomic assessment from Tao et al. From there, we used FAOSTAT country-level data on the yearly production of these oil feedstocks as potentials in 2018. Finally, population growth is used to project feedstock potential through 2100.

Industry

Industry is an extremely diverse sector with no one-size-fits all solution for decarbonization, and the industrial module is designed to address major subsectors independently, projecting demand and considering only technologies appropriate to the constraints of the specific subsector. Special attention is paid to technology characterization in the highest-emitting subsectors. As a result, industrial fuel demand is split across 15 subindustries in RHG-GEM, with specific detailed models for cement, chemicals and iron and steel. Methane from oil and gas production are considered part of the industrial sector, but accounted for in our non-CO_2 module (see the section on Agriculture, forestry and other land use and other non-CO_2 emissions).

Proxy global demand for the products of each industry is projected using regression models and historic demand, GDP, population or demand for related products. The regional supply breakdown to meet global demand is calculated by indexing historical production to changes in GDP, fuel prices, or population. A price elasticity of demand is then applied to the projections to capture sensitivity to energy prices. In addition, we calculate the historic fuel intensity of production and fit a regression model to calculate any improvements in energy intensity over time and project total energy demand. The metrics used as a proxy for demand for products in each subindustry and data sources are outlined below.

TABLE 1
Drivers of industrial demand

Industry	Demand drivers	Data source
Iron and Steel	Steel production and consumption, iron production	World Steel in Figures. World Steel Association. 2000-2023.
Chemicals	Ammonia production, petrochemical feedstocks	USGS Mineral Commodity Summaries, Nitrogen (fixed) -Ammonia. 2000-2022 IEA Energy Balances, 2023
Non-Metallic Minerals	Cement production, Lime production	USGS Mineral Commodity Summaries, Cement. 2000-2022 USGS Mineral Commodity Summaries, Lime. 2000-2022
Food, Agriculture	Total calorie supply, food production	FAOSTAT Food and Commodity Balances. 1960-2022
Motor Vehicles	Passenger vehicle production, commerical vehicle production	International Organization of Motor Vehicle Manufacturers. Production Statistics 1999-2022
Paper	Paper products production	FAOSTAT Forest Product Statistics. 1968-2022.
Non-Ferrous Metals	Aluminum production	USGS Mineral Commodity Summaries, Aluminum. 2000-2022
Construction	Building demand	Modeled metric
Oil Extraction, Coal Extraction	Fuel demand from all sectors	EIA International Coal and Coke Production. 2023. OECD Data. Crude Oil Production. 2023.
Other Industry, Other Feedstocks, Other Metal-Based Durables, Other Extraction	--	Fuel demand grows proportional to all other industries

In our generic approach, fuel for a given industry was subdivided into end-use categories (boilers/CHP, process heat, feedstock and other) based on Manufacturing Energy Consumption Survey (MECS) categorizations. A logit choice model was calibrated against the historic fuel shares for each category and used to project the future fuel shares for demand in each category. The logit is defined by the following equation:

$$s_i = \frac{\alpha_i \exp(\beta p_i)}{\sum_{j=1}^{N} \alpha_j \exp(\beta p_j)}$$

Where s is the share of total demand met by a given fuel, α is a preference parameter calibrated from historic data, β is a user-defined parameter and p is the fuel price. The β parameter is set to a higher or lower value depending on if the sector is expected to be very price sensitive; in other words, if industrial facilities can be expected to quickly switch over to the least-cost alternative, or if incumbent technologies will persist to due to either high variability in actual prices or other preferences. The α preference parameter captures any additional factors (e.g. fuel transport costs, equipment costs, labor) which may explain historic preferences for fuels but are not captured in fuel price alone.

The inverse of the equation is solved using historic fuel prices and shares to generate a time series of historic preference parameters. These preference parameters are either set constant to the historic average or allowed to trend up and down over the model period depending on the strength of the historic trend.

The model assumes that industrial equipment has long turnover times and only a fraction of the total capacity will switch fuels in a given year. A typical stock lifetime is set for each category and the inverse defines the fraction that can turnover in a given year. In each modeled year, the logit shares are applied to that fraction of the total demand, and the remaining demand shares are set equal to the overall shares in the previous year.

Additional modeling assumptions were made for major-emitting industries to capture sector-specific technologies and dynamics. These assumptions, as well as details for sector-specific demand modeling, are outlined below.

Iron and steel

There are two main stages to steelmaking: the production of iron from iron ore, which requires a reducing agent, and the conversion of iron to steel, with a limited set of technologies appropriate for each step. Ironmaking is the most carbon-intensive step in the steelmaking process, and decarbonization of the sector can be achieved with both a transition to lower-emitting technologies, as well as replacement of iron with recycled steel. As a result, the iron and steel submodule projects demand for both iron and steel and available recycled scrap, and employs a stock accounting model to determine the least-cost technology able to meet demand for each step.

Total demand for steel is projected using a non-linear inverse model with a time efficiency factor of the form:

$$Qpc = a \times e^{(B/GDPpc)} \times (1-m)^{(T-T_{max})}$$

Where the quantity of steel consumed per person Qpc is assumed to change relative to GDP per capita ($GDPpc$), with material efficiency improving over time. The parameters a, B and m are calibrated based on global historic consumption data to find the global average material demand curve. The global curve was then fit to individual regions by adjusting the per-capita saturation level (parameter a) or curve maximum (parameter B) depending on whether the region is a developed or developing economy (as characterized by the United Nations), and whether it has already exceeded global material saturation levels in line with the methodology utilized in the IMAGE model (Ruijven et al., 2016). A price elasticity is then applied to total demand. Production by region is calculated by applying the average historic ratio of regional production to consumption to each region and normalizing to total demand.

We then apply a sector-specific stock accounting model to calculate demand for total steel production by technology and retirements in every year. Demand not covered by existing capacity is met with the lowest-cost technology. This model calculates available scrap from historic production data and assumes scrap is maximally utilized to meet demand for new steel via electric arc furnace production. Any additional demand is met via ironmaking pathways, either blast furnaces or direct reduction (which may be natural gas, coal or hydrogen based).

In each year, capacity which has reached the retirement age is subtracted from the existing stock and the difference between total iron demand and total stock is assumed to be met with the lowest cost technology. Annual new deployment of a given technology is restricted to no more than doubling existing stock of the technology to reflect infrastructure and construction constraints.

Cement

Cement is an extremely carbon-intensive industry, historically requiring both high-CO_2 fossil fuels capable of producing high heat and releasing large quantities of process emissions during the chemical reaction required to make clinker, one of the main ingredients in cement. Since fuel substitution can only address a portion of the emissions from cement, solutions like carbon capture and reduction of clinker ratios are required to fully decarbonize, and the cement submodule focuses on these technologies.

Total demand for cement and lime is calculated using the same non-linear inverse model and methodology as is utilized in the iron and steel sector and historic production data. Regional production is adjusted based on price elasticity factors. Demand for energy aside from kiln process heat is assumed to grow proportional to cement demand. Total clinker demand is calculated assuming a decline in ratios from current regional levels to the current ratio in China, which has the lowest clinker ratio of any region.

The generic logit model is applied to all fuel usage categories in the cement sector except for fuel used to heat cement and lime kilns, which accounts for approximately a quarter of total energy demand in the sector. We assume that carbon capture is the most viable low-carbon alternative for cement and exclude other technology solutions in the earlier stages of development (e.g. electric kilns). We use carbon capture costs consistent with Rhodium's ICAP model, a facility-level US industrial carbon capture model developed and maintained by Rhodium Group. Data on existing cement plants with carbon capture was used to calculate the average and standard deviation of prices for this technology and generate a normal curve, reflecting uncertainty in plant-level costs. In each year, the cost of emitting a ton of carbon is compared to the price curve and the fraction of the cost curve which falls below the carbon cost is assumed to be the share of total cement plants which have carbon capture in that year.

Chemicals

We divided fuel use in the chemicals industry into three major sectors: ammonia, methanol, and high-value chemicals (HVCs). Demand for ammonia is projected using a log-linear regression on global population and historic production. Production is downscaled to regions based on relative changes in population and fuel costs. Chemical fuel feedstocks are used as a proxy for HVC demand and projected using a log-linear regression on global GDP and historic quantities. Production is downscaled to regions based on relative changes in fuel prices and GDP. Methanol and demand for non-process or feedstock energy is assumed to grow proportional to demand for HVC's.

Process heat in the ammonia and methanol sectors was assumed to be used primarily as a feedstock and heat source for the generation of hydrogen, which is required for the chemical reaction process. The fuel used for hydrogen generation is removed from the chemicals sector and included instead in the REEM. We calculate hydrogen demand for the chemical industry based on ammonia and methanol production, and send this to the REEM where hydrogen production mix is determined based on a least-cost optimization. Given that urea and methanol require a source of carbon, we assume that hydrogen for those products is produced with carbon-based hydrogen (including with capture). Remaining fuel usage in the chemicals sector is determined using the logit approach described above.

Refining

In the oil refining sector, which currently accounts for 33% of global hydrogen demand, we focus on opportunities for clean hydrogen deployment and carbon capture. RHG-GEM model projects demand for fuel use in refineries use based on global oil product demand and historic refinery gain and calculates the amount of associated hydrogen demand required to remove sulphur from crude oil. The resulting hydrogen demand is sent to the REEM, where the least-cost mix of hydrogen technologies are deployed to meet demand. We exclude hydrogen supplied by refinery by-products, since this is sometimes produced from integrated systems that would be difficult to retrofit. We model carbon capture on fluid catalytic cracker units using the same approach as we do for cement. Capture costs are based on Rhodium's ICAP model.

Food and agriculture

Regional food demand in terms of calories supplied per capita is assumed to grow with GDP per capita. A global log-log model is fit to historic calorie per capita data and projected forward, and a saturation point is assumed at the current calorie per capita consumption level of the United States. This trend is then applied to the current regional consumption levels in order to project regional demand, and regional demands are summed to determine global demand. Food is assumed to be highly traded, with global demand being met with supply from any region. Current regional supply fractions are calculated from historic production data, and these supply fractions are scaled and normalized over time with changes in regional demand, then applied to global demand in order to calculate regional production levels in terms of tons of food produced. The same calculations are applied to scale energy demand from the agricultural sector over time.

Paper

Global paper demand is calculated by applying a log-log regression to global historic paper production per capita and GDP per capita. Regional trendlines are set by applying the global trend and scaling the intercept to match current regional production levels. A saturation point is set at the current production levels for the United States, which has both steady production levels and the highest current levels of production per capita.

Non-ferrous metals

Aluminum is a key input for many higher-level products, with the bulk of demand coming from buildings, vehicles, electric power, and consumer goods. Thus, demand for aluminum is projected to grow with demand in these sectors. Historic aluminum demand per unit demand for each end use is calculated by applying current end-use fractions to global historic aluminum production data and dividing by demand indicators for each end use—vehicle production, total electricity demand, total buildings energy demand, with population used as a proxy catch-all for consumer goods. This aluminum material intensity is then applied to global projections of each demand indicator to calculate global aluminum demand. Regional production fractions are then calculated by scaling current production fractions over time with relative changes in GDP and electricity prices, assuming aluminum production will grow more in areas with high economic growth and low electricity prices.

Road vehicles

Global demand for new vehicles is calculated in the GEM Transport module. Regional production fractions are calculated from historic production data. These fractions are scaled over time with relative changes in regional GDP and demand, normalized, and then applied to global demand quantities to obtain number of new vehicles produced by region.

Oil and coal extraction

Total fuel demand from oil and coal extraction is assumed to grow proportional to economy-wide demand for these fuels. Production quantities are obtained by multiplying the historic ratio of extracted fuels to total demand by future demand for fuels. For coal, regional production fractions are calculated from historic data and applied to production projections, assuming relative production fractions do not change over time. For oil, regional production fractions are calculated from the GEM Oil and Gas module outputs of oil production by region.

Other industries

“Other industries” represents fuel demand from various uncharacterized industrial sectors—high level manufacturing of consumer durables, textiles, leather, wood and other products, and unspecified extraction. In addition, some countries do not report sector-specific fuel demand in the IEA Energy Balances, and all industrial energy demand is categorized as “other” and represented here. Since all fuel demand in other industries represents either such uncharacterized demand or demand from refinement of basic materials characterized elsewhere, fuel demand in “Other Industry” is assumed to grow proportional to fuel demand from all other industrial sectors.

Transportation

The transport model projects demand for passenger and freight transportation based on demographic and economic drivers. For on-road transportation, we take a technology rich, stock-accounting approach with an aim to capture new technology adoption based on relative costs and performance, taking into account policy, infrastructure barriers, and consumer behavior. In air and marine transportation, we take a simpler approach due to data constraints, but similarly capture cost, efficiency and infrastructure for a range of conventional and novel technologies.

Light-duty vehicles (LDV)

LDV fuel consumption is calculated using a stock-based approach for vehicle kilometers travelled and average fuel economy of the existing stock. This submodule uses a vintage stock accounting model to calculate the sales and stocks across regions. LDV stocks per capita are projected using the Gompertz curve related to GDP per capita and vehicle ownership. The survival curve is subsequently applied to calculate the surviving stock and finding sales required to satisfy the demand. The historical stocks are calibrated to 2016 IEA Mobility Model for the Transport Model (MoMo) data. The market share of the sales is determined using a multinominal logit based on EIA's WEPS model, with attributes such as upfront cost of vehicle price, fuel cost, fuel economy, make-and-model and fuel availability. After the market shares are computed, the average fuel economy is adjusted to meet the fuel economy standards. The LDV fuel consumption is then calculated by multiplying average stock fuel economy by the stock and average vehicle kilometer traveled by each vehicle.

On-road freight

Freight (including passenger buses) are categorized into three classes based on the gross weight of the vehicle (GVW) — light (< 3.85 tons), medium (3.85 – 16.5 tons), and heavy (>16.5 tons) trucks. Medium and heavy trucks are further split based on their operation range into short-haul (<500 miles) and long-haul trucks (>500 miles) based on the US Vehicle Inventory and Use Survey.

Along with the projected travel demand for trucks, a stock accounting model is used to project future sales and stocks. The module consists of seven vehicle technology types—gasoline, diesel, natural gas, LPG, battery electric vehicle (BEV), plug-in hybrid electric (PHEV) and fuel cell electric vehicles (FCEV). We assume FCEVs will be more suited for medium and heavy trucks due to FCEV's longer range, faster refueling times, and lower risk of lost cargo capacity. The market share of sales by drivetrain is determined by using a logit choice model based on the total cost of ownership (TCO) of the trucks (see the Industry section for logit equation). TCO for each technology is calculated for the first user over a period of five years using upfront cost of the vehicle, resale price, infrastructure cost (for BEV and FCEVs), maintenance cost and fuel cost per mile.

Further, we assume fuel economy standards currently on-the-books are met, plus moderate fuel economy improvements for all regions through 2050, based on expert judgement and historical trends. For both LDV and freight, we assume all zero emission vehicle policies are met, including mandates and subsidies.

Marine

Domestic marine travel demand is projected using GDP per capita and oil price. International marine demand is projected by growth in energy commodities (coal, LPG, natural gas and petroleum product) and oil price. The future share of fuels in marine consumption is determined using a logit choice model based on the TCO of different powertrains in shipping. The TCO is calculated based on IEA assumptions for base ship cost, fuel cell/engine cost, fuel storage, infrastructure and delivery costs.

Aviation

For passenger air travel, revenue passenger miles (RPM) per capita is projected based on the historical relationship between GDP per capita and demand. RPM per capita is assumed to follow an s-curve shape to reflect more rapid growth as regions develop and saturation at higher levels of income. GDP per capita is also used to project revenue ton miles for freight air demand. The future shares of conventional and sustainable aviation fuels are determined by a logit choice function based on projected fuel prices.

Buildings

Residential and commercial energy demands by fuel are calculated based on projected changes in GDP, population, and fuel prices. As shown in the formula below, each service demand is assigned a socioeconomic driver of growth as well as an elasticity factor to inflate/deflate demand growth above/below the driver alone. Demand is also subject to changes in the weighted-average fuel price and a fuel price elasticity.

$$demand_t = demand_{t-1} * (driver_t/driver_{t-1})^{driver\ elasticity} * (price_t/price_{t-1})^{price\ elasticity}$$

Historical energy consumption by energy service is calibrated to data from GCAM. For each service demand, region and year, fuel mix is determined using a logit choice model calibrated against the historic fuel shares.

SECTION 2: PROBABILISTIC PROJECTIONS

RHG-GEM is an integrated platform that produces fully probabilistic policy, socioeconomic, energy price, technology cost and behavioral projections of the energy system and emissions. We do so using a Monte Carlo Analysis (MCA), which relies on repeated random sampling to estimate a probability distribution of outcomes. Global emissions are then fed into the FaIR model to produce internally-consistent probabilistic global average temperatures.

Emission uncertainties

We parameterize the following sources of socioeconomic, energy market, and behavioral uncertainty as inputs to the energy system model. Policy and climate uncertainties are discussed in subsequent sections. To define our sensitivities, we draw on the best available third-party data and research. For data sources with probabilistic projections, we sample from those distributions. Otherwise, we establish probability distributions to be consistent with the most recent research and to reflect the range of market and economic uncertainties.

- GDP per capita: GDP per capita data is taken from Stock, Watson, and Mueller's Bayesian latent factor modeling of international long-run growth. Their projections produce a joint predictive distribution of per capita GDP for 113 countries through the end of the century. We sample jointly distributed country-level GDP per capita from this dataset and aggregate up to the RHG-GEM regional level where needed.
- Population: Population data through 2100 is taken from the UNDP's probabilistic global projections. We assume independence of GDP per capita and population due to a lack of reliable information on their joint distribution.
- Oil and gas markets: We consider a distribution of oil and natural gas prices based on the historical range, with median prices of $100 per barrel for Brent crude and $3.8 per mmBTU for Henry Hub natural gas. Henry Hub prices are adjusted by region based on the historical relationship between Henry Hub and other regional market prices.
- Renewable technology cost: Overnight capital and operating costs for key renewable technology costs are based on the National Renewable Energy Laboratory's (NREL) Annual Technology Baseline. We construct a probability distribution of costs based on the NREL's Conservative, Moderate Technology Innovation, and Advanced Technology Scenarios for solar, wind, and utility-scale storage. Costs are jointly sampled for wind and solar, while utility-scale batteries are sampled with electric vehicle (EV) battery costs, with the assumption that they continue to rely primarily on lithium-ion technology.
- Electric vehicle battery costs: A major factor in EV adoption for passenger vehicles is upfront costs. We therefore consider uncertainty in the year cost parity is achieved between EVs and conventional vehicles between 2025 and 2040. For freight we consider uncertainty in the cost of lithium-ion batteries. We construct a probability distribution based on AEO 2023 reference and BNEF battery cost projections. We

assume battery costs for the suite of heavy-duty EV technologies modeled in RHG-GEM match these reduction pathways.

- Emerging climate technologies (ECTs) learning rates: Currently, ECTs are typically more expensive than their fossil-fuel incumbents. Over time, these costs are expected to come down as a function of deployment, often referred to as a learning rate or experience curve. For direct air capture and clean H2 technologies, we consider a range of learning rates – defined as the cost reduction for each doubling of deployment - to reflect uncertainty in future cost reductions.
- "Friction" in clean technology uptake: Clean technology faces many non-cost barriers today that may continue to slow their adoption. For passenger and freight EVs, this includes insufficient charging infrastructure—real or perceived—limited model availability, and political politicization. For clean electricity generation, barriers include lengthy permitting times, insufficient transmission, and public opposition. We capture these barriers in aggregate as uncertainty in the pace of deployment. This is modeled as a shift in the deployment curve for EVs and as an increase in the construction time for wind and solar projects.

SECTION 3: CLIMATE POLICY PROJECTIONS—WHAT ARE WE ON TRACK FOR?

As more and more countries adopt emission reduction targets or net-zero emission pledges, the gap between current policies and the mitigation actions needed to achieve these goals continues to widen. Assessing that gap is crucial and Integrated Assessment Models (IAMs) can contribute by projecting the evolution of GHG emissions and temperature over the next century under alternative policy developments. IAMs generally project where current policies (and sometimes announced policies) take us if no further action is implemented. These current policy pathways are compared with stylized policy scenarios where the world meets specific targets (e.g. 1.5°C warming) to alert of this policy gap and spur governments into further action. But policy is not static. It is the product of evolving social, economic, and political drivers. Climate policy will continue to develop over time, and quantitative assessments of this evolution are critically missing for decision-makers, who invest in new equipment, processes, and technologies across the world.

The latest addition to RHG-GEM, the Climate Policy Projections (CPP) aims to fill this gap. Based on an econometric model of climate policy, the CPP charts the likely evolution of climate action over time. Underlying Rhodium's CPP is a panel data analysis of policy evolution in 51 countries from 2000 to 2020. Rather than a deterministic forecast, the CPP is a policy-modeling tool that responds dynamically to projections of political and socioeconomic drivers. Incorporated into Rhodium's suite of global energy system, GHG emissions and temperature models, it allows us to answer the question: What are we on track for?

What drives a country's climate action?

As climate change rises on the political agenda, research has increasingly focused on the forces influencing climate policy action at different levels of government. From quantifying local lobbying efforts to multi-country comparisons of carbon pricing policies, a review of this broad political economy literature suggests that climate policy is linked to three types of factors:

Economic

Higher levels of GDP per capita tend to be associated with more ambitious climate policy. Wealthier economies have more resources to devote to climate mitigation and can afford to invest in new technologies. They also tend to have greater historical emissions, implying higher responsibility. Climate policy is also responsive to energy prices. With higher fuel prices, affordability and competitiveness concerns quickly come to the forefront of the political agenda. On the other hand, reliance on fossil fuel revenues (so-called fossil fuel rents) reduces a country's likelihood of implementing policies curbing their extraction or use.

Political

A rise in public awareness of climate change and its impacts has been a critical factor in bringing the issue to the recent political agenda, increasing policy action. Organized private interests have been shown to actively mobilize and lobby against more ambitious climate policies historically, on the basis that they increase costs and affect profitability (e.g. fossil-fuel extraction and supply, fossil-based power generation, energy-intensive industries). On the other hand, as the economic opportunities from the energy transition arise, it is likely that a growing influence of clean technology lobbies could influence climate policy action positively.

Institutional

The influence of these political forces on climate action is catalyzed by a country's institutions. Good governance tends to be linked to more transparent formulation and implementation of policies, more independence from private influence, less subject to corruption, and more closely related to public opinion. Good quality institutions should therefore deliver more climate action as public concern rises on the topic.

In a panel data analysis, we relate these drivers to the historical evolution of climate action to verify and quantify these mechanisms.

Historical evolution of climate policy

Climate policy has evolved differently across the world and policy instruments differ widely. Our quantitative approach to the CPP delivers a single measure of climate action (both its coverage and stringency) which can be consistently compared across countries and over time. Studies have used different proxies for this: Most rely on GHG emissions reductions as an indicator of climate change mitigation. But emissions are directly linked to economic output and are therefore greatly affected by non-policy factors (e.g., recession, natural disaster, pandemic). Others focus on countries that have implemented a carbon price as a comparable indicator of climate ambition—a method that discounts climate policy implemented through other instruments (subsidies, regulation, etc.). Another common method is to consider "policy density", i.e., the number of climate policies and laws implemented in one country, abstracting from the effectiveness or at least ambition underlying these policy packages.

For our analysis, we built a novel national index of climate action, based on the OECD's Climate Actions and Policies Measurement Framework[1], a structured and harmonized database of climate policies across countries and years. We base our analysis on the 2022 database version, covering from 2000 to 2020 and 50 countries participating in the International Programme for Action on Climate (namely OECD members and accession candidates, G20 countries and the European Union). Several global databases of climate policies are publicly available, but the CAPMF is the most comprehensive *harmonized* database. It brings together 56 policies and climate actions, ranging from sectoral instruments (e.g. solar feed-in-tariffs or minimum efficiency performance standards for appliances), to cross-sectoral policies (e.g. carbon prices, targets) as well as international actions (e.g. participation in climate agreements). The database tracks the implementation of each of these 56 policies across countries, as well as their stringency using a normalized scale: from zero when a policy is not in place, to 1 capturing the most stringent implementation across all countries and years in the database.

For each country in the database, we construct an aggregate climate policy index, as a weighted average of each of the policies' stringency in each country and year. Since the CAPMF deliberately includes both climate mitigation policies and non-climate policies that have climate mitigation benefits, we must assign weights to each policy to give more importance to those directly intended to reduce emissions (see Table 2).

[1] Nachtigall, D., et al. (2022), "The climate actions and policies measurement framework: A structured and harmonised climate policy database to monitor countries' mitigation action", OECD Environment Working Papers, No. 203, OECD Publishing, Paris, https://doi.org/10.1787/2caa60ce-en

TABLE 2
Policy weights in Rhodium's Climate Policy Index

Policy classification	Weight in index	Example policies in the CAMPF
Market and regulatory instruments directly aimed at reducing emissions	1	Prices, taxes, deployment subsidies, standards
Enabling instruments to facilitate emission reductions but not reduce them directly	0.75	Planning for renewables, R&D subsidies
Non-constraining instruments with aspirational value	0.5	Targets, signatures of international agreements
Actions with informational or advisory value	0.25	Labels, reporting commitments, voluntary mechanisms
Non-climate policy instruments	0[2]	Speed limits, rail expenditures

Our final index captures a general increase in climate policy ambition within and across sectors, in a consistent way which allows for comparison both across countries and over time.

Climate policy projection drivers

Using a panel data analysis, we estimate how various drivers (economic, political, institutional) impacted climate policy over the 20-year time period of analysis and across 50 countries. The econometric model is presented in Box 1.

Box 1: The econometric model
We chose a country-fixed effect model to control for unobserved heterogeneity between countries:

$$Idx_{it} = \bar{\gamma}\overline{D_{it}} + \alpha_i + \varepsilon_{it}$$

Where:

i,t	country, year
Idx_{it}	Dependent variable: Climate Action Index
$\overline{D_{it}}$	Climate action drivers
$\bar{\gamma}$	Associated coefficients
α_i	Country-specific fixed effects
ε_{it}	Error term

We test a range of drivers and different model specifications. Table 3 summarizes the results. Our measure of fossil fuel lobby and a country's income level have historically been the largest drivers of climate action. While higher GDP per capita results in more climate action, a high reliance on oil, gas and coal in the energy system tends to lead to less ambitious policies. Economic dependency on oil (i.e., higher oil rents) and a large share of manufacturing in GDP both have historically negatively impacted climate action. In contrast, higher oil prices have spurred more climate action, although the analysis suggests a delayed policy reaction to oil prices.

Institutional drivers (government effectiveness and regulatory quality) do not add explanatory power to the model, regardless of the specification chosen, and neither do our measures of climate technology industrial leadership (patents)

[2] We assign a weight of 0 to policies with incomplete data over the period, to avoid artificial breaks in the policy index (i.e., fossil fuel subsidies reforms and energy efficiency policies reported only after 2010).

and public awareness (media coverage). We expect public opinion (awareness but also concern) to have played a role in policy formation but there is limited data available to test this in a robust way[3].

Based on the results of the econometric analysis, we build our Climate Policy Projections tool, where future climate action in a given country or region is a function of the selected drivers above, namely GDP per capita, the shares of oil, gas, and coal in energy demand, oil rents, the share of manufacturing in value added and the lagged oil price. The relationships between drivers and climate action are informed by the coefficients of the fixed effect model. We also account for uncertainty in our projections (i.e., capturing the drivers we do not currently model) using projected residuals, randomly sampled from the results of a bootstrapping exercise[4].

TABLE 3

Results of the panel data analysis

Drivers	Variable or proxy (and source)	Results of analysis	Inclusion in CPP
Income	GDP per capita (World Bank)	Positive relationship, significant (1% level)	Yes
Oil price	WTI Brent crude oil price & lags, (IEA)	Positive & small relationship with lagged variable, significant (1% level)	Yes, lagged
Economic reliance on fossil fuels	Oil rent, Gas rent, Coal rent (World Bank)	Negative & small relationship, only oil is significant (1% level)	Yes, oil rent only
Fossil fuel lobby	Share of oil/gas/coal in energy demand (IEA)	Negative significant relationship for all three (1% level)	Yes
Weight of industry in economy	Share of manufacturing in Value-Added (%) (World Bank)	Small negative and significant relationship (5% level)	Yes
Industrial leadership in cleantech	Number of clean energy patents (IEA)	Not significant	No
Good governance	Government Effectiveness & Regulatory Quality Indices (World Bank)	Negative, contrary to hypothesis, significant for government effectiveness (10% level)	No
Public awareness of climate change	Number of media articles on climate change or global warming + lags, (Media and Climate Change Observatory)	Very small positive relationship but not significant.	No

Projecting policy action in the RHG-GEM

The Climate Policy Projections are integrated as a module into RHG-GEM. The module endogenously projects the evolution of climate policy in each of the RHG-GEM's 16 regions and countries, based on socio-economic inputs (GDP, population, fuel prices) and on the evolution of the energy system itself via feedback from other RHG-GEM modules. The projected policy pathways feed into the decision-making process throughout the model: as climate policy becomes more or less stringent in a given scenario, final demand consumers (household, industry, transport) and suppliers (electricity generation, fuel production) can adapt their technology choices to more or less carbon-intensive options. Figure 2 represents the integration of CPP and its linkages in RHG-GEM.

For simplicity and transparency, these projections are translated into regional carbon prices in the model. Regional starting points in 2021 are scaled to the EU-ETS carbon price based on the policy ambition index in that year relative to the EU. In regions with existing carbon prices, the carbon price is applied as an economy-wide tax. In other regions, we adjust carbon

3 International public opinion surveys on climate change vary in geographical coverage and are not available historically on a yearly basis. They also differ in the wording of questions and could not be used to reconstruct a large enough panel to include in our analysis.

4 Our bootstrap method estimates our panel data model 1000 times, resulting in 50,000 20-year sequences of residuals, from which projections can be randomly sampled.

prices in the electric power sector down and make a comparable upward adjustment in the transport sector. This reflects the evidence that electricity sector policies have lower effective carbon prices than transport policies. The weighted average economy-wide carbon price remains the same, reflecting overall regional ambition.

The full integration of CPP as a module in RHG-GEM allows us to project the likely evolution of policy in a dynamic way which is consistent with the underlying economic, energy system and technological assumptions. Combined with the MCA of the major uncertainties behind the clean energy transition, we can provide probabilistic ranges of GHG emissions and temperature outcomes, inclusive of a dynamic climate policy evolution. With the CPP, RHG-GEM is the first model to provide an endogenous, internally consistent probabilistic answer to the question: What are we on track for?

Current policies in RHG-GEM

In addition to our stylized projections of future policy, we also include current policy from all actionable and quantifiable existing national policy that we expect will have meaningful emissions impact beyond what the projected policy will deliver. For example, we don't anticipate a carbon price to provide a good proxy for targeted subsidies for electric vehicles or emerging clean technologies. To remain consistent with United Nations guidelines for reporting the impact of current measures, we include only policies that have been finalized and adopted. We do not include aspirational goals or economy-wide targets that have yet to be solidified in specific, actionable policy. We include sub-national policies where relevant—for example, state-level ZEV mandates in the United States. The following is a non-exhaustive list of policies included in our RCO 2023:

- Renewable portfolio standards and clean energy targets
- Fuel economy and CO_2 standards for LDV and freight
- Zero emission vehicle mandates
- ECT subsidies

SECTION 4: TEMPERATURE OUTCOMES: THE FINITE-AMPLITUDE IMPULSE RESPONSE (FAIR) MODEL

RHG-GEM's emissions modeling is coupled with the FaIR model to provide probabilistic global temperature rise. FaIR simulates the global climate's response to global emission, considering climate uncertainty. This simple model provides accurate representation of the climate's response to emissions, while minimizing the computational burden of running thousands of simulations in a Monte Carlo framework.

Model description

The Finite-amplitude Impulse Response (FaIR) model is a reduced-complexity climate carbon-cycle model representing the global average climate system, taking into account the timescales of carbon and heat exchange, and of different greenhouse gas (GHG) and aerosol species. It is a lightweight, fast, transparent, and simple model that accurately reflects the climate response to emissions. FaIR calculates atmospheric GHG concentrations from GHG emissions, the effect of changing concentrations on radiative forcing (how much the planet's energy imbalance changes), and ultimately the change in global average temperature resulting from the changing energy imbalance. This model was used extensively in the IPCC's 6th Assessment Report and was identified by NASEM as an exemplar of a simple climate model meeting criteria for social cost of greenhouse gas calculations. These criteria include transparency, simplicity, and ability to accurately and probabilistically represent climate and carbon cycle systems and their uncertainties in a manner consistent with IPCC assessments and insights from more complex Earth system models. Note that FaIR does not contain sub-global or regional patterns, such as the hemispheric nature of aerosols, nor does it contain internal variability (e.g. weather) or tipping point representation but is rather a smooth representation of global averages.

For this report, we use FaIR version 1.6.4, which is a slightly updated version from that used in AR6 but with identical results. A description of how GEM emissions were prepared and how FaIR simulations were executed follows.

Emissions

Global emissions were taken from RHG-GEM MCA trials and reflect the probability distribution of global GHGs through 2100 under uncertainty. Emissions for 6 gases from GEM in CO_2-equivalent units were disaggregated, unit converted, and formatted into the format expected by FaIR (a 39-species array by year).

To represent historical emissions and emissions of gases not included in GEM, emissions from the Reduced Complexity Model Intercomparison Project (RCMIP) were obtained for the SSP2-4.5 emissions scenario, which includes historical emissions and a projection of future emissions for a middle-of-the-road mitigation future in which radiative forcing reaches ~4.5W/m2 by 2100. SSP2-4.5 emissions are used until year 2022, when GEM emissions projections begin, at which time projected GEM emissions for each of the included gas species are delta-shifted to the SSP2-4.5 level and carried forward based on GEM trends. The resulting emissions are used as inputs to FaIR in combination with climate parameters representing climate uncertainty, as described in the next section.

FaIR simulations

A key feature of FaIR is its ability to run quickly, and efficiently produce probabilistic time series of the temperature response to GHG emissions that captures the uncertainties in the climate system. The response to emissions is captive to uncertain values of carbon and heat uptake by the ocean, climate sensitivity, and radiative forcing, to name a few factors. Many of these uncertain parameters are exogenous to FaIR and can be set by the user to sample a physically plausible range, for example. Here we have used a set of calibrated input parameter samples that were developed for use in the AR6 to determine the global mean temperature response to emissions, reflecting the current best estimates of climate uncertainty (see Forster et al. 2021 Box 7.1 and Chapter 7 Supplementary Material 7.SM.2 for additional details).

The FaIR input parameter samples were chosen following a set of constraints applied to a 1-million-member ensemble of emissions-driven FaIR simulations over years 1750 - 2019, as described in Ch. 7 of AR6 WG1 and its Supplementary Material (Section 7SM.2). The initial parameter draws were sampled from assessed and/or published uncertainty ranges of effective radiative forcing (ERF), the climate response (surface and deep ocean effective heat capacities, efficacy of ocean heat uptake, heat transfer coefficient between the surface and deep ocean layers, and climate feedback parameter), and the carbon cycle (airborne fraction of CO_2, and change in airborne fraction of CO_2). The resulting constrained parameter set consists of 2,237 samples of 15 parameters. Together the resulting climate simulations satisfy criteria for matching the following: the trend in historical global average temperature, the assessed historical ocean heat uptake, 2014 atmospheric CO2 concentrations, and airborne fraction of CO_2 concentrations in transient CO_2 increase simulations. The climate simulations run with this parameter set are consistent with the assessed ranges of equilibrium climate sensitivity (ECS) and transient climate response (TCR), and the ranges of global average temperature change for the AR6 emissions scenarios (see Ch 7 Cross-Chapter Box 7.1 of Forster et al. 2021). Version 1.0 of the FaIR parameter set was used. The final parameter set consists of 2,237 samples that give FaIR simulations with physically plausible and historically consistent time series of global average temperature.

SECTION 5: MONTE CARLO ANALYSIS

Monte Carlo Analysis (MCA) is a mathematical technique used to estimate possible outcomes in a highly uncertain system. The method relies on repeated and simultaneous sampling of uncertain input parameters, represented by probability distributions, which in turn generates a probability distribution of outcomes. MCA is well-suited for producing probabilistic projections of the energy and climate systems, both of which are highly complex and dependent on numerous uncertainties.

Sampling strategy

We leverage Latin hypercube sampling (LHS henceforth) to construct samples for uncertain parameters. The decision to employ LHS is rooted in its ability to systematically explore the entire spectrum of uncertainty associated with these parameters while simultaneously minimizing the number of samples required. Unlike random sampling methods, LHS ensures a more even coverage across the range of each uncertain parameter, providing a representative set of scenarios for our analysis.

We ran 4726 MCA simulations, which provided a reasonable level of precision in global emissions outcomes while minimizing computational burden. Considering that each GEM simulation requires an average of 3 hours to run, we addressed the challenge of runtime constraints by parallelizing our simulations. To achieve this, we utilized GAMS engine, a Software as a Service (SaaS) provided by GAMS, accessed through their API. This parallelization strategy allowed us to run 1200 simulations simultaneously, significantly optimizing our overall runtime.

An integrated energy-climate MCA

Uncertainty in climate policy projections

The climate policy projections are derived internally to RHG-GEM, enabling uncertainty in parameters and assumptions above (e.g., GDP, population and oil prices) to feed into the evolution of climate policy. Two-way interactions between the energy system and the climate policy projections are enabled through running iterations of RHG-GEM, ensuring consistency between the emission pathway and climate policy projections under a given set of sampled parameters. We also model uncertainty in our climate policy projections (i.e., capturing the drivers we do not currently model) using projected residuals, randomly sampled from the results of a bootstrapping exercise. Lastly, we capture uncertainty in the estimates of the regression parameters.

Pairing of emissions and climate uncertainty

To manage computational resources, a method was established to link RHG-GEM emissions uncertainty with a representative sample of FaIR climate uncertainty. A full pairing of the 2,237 FaIR samples with the all RHG-GEM emissions pathways was not viable due to the excessive number of simulations required. Instead, each RHG-GEM emissions pathway was paired with 7 randomly selected climate parameter samples with replacement, to ensure an adequate spread of the climate uncertainty is accounted for each emissions pathway. The FaIR model was then executed for each emissions-climate parameter pairing, resulting in a set of 33,066 climate simulations. For the purpose of analysis, the simulation data was confined to the years 2022 - 2100.

Uncertainty decomposition analysis

Beyond reflecting the uncertainty in global emissions pathways and temperature outcomes, the MCA allows us to explore the contributions of each of the uncertain parameters considered on model results. The MCA framework is useful to move away from punctual sensitivity analysis of each parameter, towards a global sensitivity analysis, which considers all parameters and their interactions on our modeled outcomes.

Following Saltelli et al. (2008), we perform multivariate regression analysis on our MCA results and compute the Standardized Regression Coefficients (SRC) in order to determine the importance of each of our uncertain parameters on our model outputs. Although the relationships between inputs and outputs are not linear in the RHG-GEM, we do not aim to quantify that relationship through the linear regression, but rather to inform our results on the relative importance of each uncertain parameter on the outcome.

We perform two regressions, the first on temperature outcomes, and the second global emissions, as follows:

$$T_{i,t} = \beta_{T0} + \beta_{T1} E_{i,t} + \sum_{j} \beta_{Tj}\, X_{j,i,t}$$

$$E_{i,t} = \beta_{E0} + \sum_{k} \beta_{Ek}\, Z_{k,i,t}$$

Where T and E represent the global mean temperature and global cumulative GHG emissions in sample i and year t respectively, while $X_j$are the j uncertain climate input parameters to the FaIR model, and Z_k are the k uncertain input parameters to the RHG-GEM. β_T and β_E therefore represent the regression coefficients of the multivariate regressions on global mean temperatures and global cumulative emissions respectively. To avoid multicollinearity issues, we only include a single parameter in a set of jointly sampled uncertainties (e.g. renewable capital costs as a whole). We also exclude uncertainties with negligible impacts on global emissions. We normalize the data inputs to the regression so as to obtain regression coefficients which are already standardized to the variance of our model outcome and can be used directly for sensitivity analysis.

The R-square statistic, which reflects the goodness of fit of the linear model and can be interpreted as the fraction of the variance explained by our regression is high - 0.73 for temperatures in 2100 and 0.75 for emissions. The uncertainty parameters we include as independent variables all show statistical significance at the 95% level. Given our large sample size (N=4726 for global emissions and N= 33085 for temperature outcomes), the SRC can be interpreted as the relative first-order contribution of each parameter to the portion of the variance explained by our model. In other words, we cannot capture the full effect of each parameter's variance on the variance of the model outcome, but these higher order effect (interactions between parameters) are captured in the unexplained portion of the variance.

SECTION 6: AGRICULTURE, FORESTRY AND OTHER LAND USE AND OTHER NON-CO_2 EMISSIONS

RHG-GEM provides comprehensive, methodologically consistent projections of economy-wide emissions of all six gases included under the Kyoto Protocol (CO_2, methane, nitrous oxide, hydrofluorocarbons, perfluorocarbons, and sulfur hexafluoride), including for agriculture, forestry and other land uses (AFOLU). For most AFOLU and non-CO_2 emissions, changes in emissions over time are driven by changes in the underlying socioeconomic drivers (e.g., population and economic growth). Unlike for energy CO_2, we assume no evolution in climate policy throughout the projection period (with the exception of HFCs). There is not yet enough historical evidence of climate policy applied across geographies in these sectors to provide robust data to model the potential evolution of future policy using our Climate Policy Projection model. As climate policy deploys across these sectors in the coming years, we hope that data collection will allow us to include these sectors in our CPP. For now, we assume that emission rates remain consistent with today's levels. Below we outline the specific methods we apply to each sub-sector category.

Agriculture, forestry and land use GHG emissions

To establish a methodologically consistent historical emissions inventory for AFOLU, we use Food and Agriculture Organization (FAO) data, which we align with inventory categories defined by the Intergovernmental Panel on Climate Change (IPCC). For projections extending to 2100, we start with emission trends aligning with scenarios modeled by the International Institute for Applied Systems Analysis (IIASA) in their GLOBIOM-G4M projections. This scenario is based on SSP2, which describes a world in which agricultural yield improvements are more pronounced in developing economies, gradually converging with those in developed nations. It does not assume that the world's sustainability goals are met. In this scenario, emissions from AFOLU are projected to decrease through 2100, due in part to ongoing afforestation efforts and productivity enhancements, counterbalanced by population growth and consequent land scarcity.

We align the emissions trends for CO_2, methane, and nitrous oxide from IIASA's projections with the underlying socioeconomic assumptions (e.g. economic and population growth) and uncertainties in RHG-GEM, which provides a range of potential emission outcomes for AFOLU. Specifically, we take the range of scenarios that assume no carbon price is applied in this sector throughout the projections and assume biomass prices ranging from $0-60 per gigajoule. This does not capture the full range of potential emissions from this sector, however, as we do not capture the effect of potential climate or sustainable development policies that may shape the future of GHG emissions and removals from this sector.

Industry

For vented and flared methane emissions from coal, oil and natural production and transportation, we take coal, oil and gas production and consumption outputs from RHG-GEM and apply regional emission factors from the International Energy Agency (IEA). For the United States, we apply emission factors from Taking Stock 2023, reflecting current policies and regulations targeting emissions in production, distribution, and processing as of June 2023. We have not incorporated methane emissions abatement policy from the rest of the world due to a lack of modeling of how recently announced policies existing policies will impact emissions. There is not yet sufficient evidence in the historical record of methane abatement from oil and gas to allow us to incorporate it into our econometric Climate Policy Projection. For now, we assume current emission-intensity rates continue at historical rates throughout the projection period.

The projection of nitrous oxides follows a similar behavior to CO_2 emissions and activity data from the relevant sub-industries projection in RHG-GEM industrial module. In a similar way, the projection of F-gases emissions is correlated with regional GDP per capita, reflecting their association with industrial production and the manufacturing of specific products.

Hydrofluorocarbons

We assume global implementation of the Kigali Amendment of the Montreal Protocol, which provides a legally binding pathway for phasing down the consumption and production of hydrofluorocarbons (HFCs). We apply the Kigali implementation scenario from the recent Velders study, which finds that HFC emissions under Kigali implementation decline to 1 gigaton of CO_2 equivalent by 2050 and then level off by 2080 remaining below 0.5 gigatons up to 2100.

Disclosure Appendix

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