# Emerging Climate Technology Baselines: Technical Appendix

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In 2021, Breakthrough Energy established its Emerging Climate Technology Framework (ECTF) as a tool to incentivize early stage investment in Emerging Climate Technologies (ECTs), including sustainable aviation fuel, direct air capture, clean hydrogen and long-duration energy storage. The ECTF is used to estimate the impact of an investment in an ECT project based on two key metrics: reductions in the green premium for each ECT (the relative cost difference from their primarily fossil incumbents) and the catalyzed emission reductions that result from the green premium reduction's impact on accelerating global deployment. As an input to the ECTF, Rhodium has developed a set of ECT deployment baselines using Rhodium's Global Energy Model (RHG-GEM).

This document provides a detailed overview of: 1) Rhodium's Global Energy Model; and 2) the 2022 ECT baselines modeled in RHG-GEM for use in Breakthrough Energy's ECTF model. Each year Rhodium will update RHG-GEM and our ECT baselines based on improved data and updated market and policy assumptions.

## Global Energy Model

To model global emerging climate technology (ECT) deployment under baseline conditions, we use Rhodium's Global Energy Model (RHG-GEM), a modified version of the detailed 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 to capture emerging clean technologies (ECTs) and enhancing it to be able to robustly capture a range of policy and energy market uncertainties. We provide a brief overview of our modifications below, with additional detail in subsequent sections. Unless otherwise stated below, we use EIA's IEO2021 reference case assumptions in our projections.

### Modifications to WEPS

- Clean technology characterization: Rhodium expanded the set of novel clean technologies available in WEPS, with a focus on clean hydrogen production, sustainable aviation fuels (SAF) production, and direct air capture (DAC). Long duration energy storage (LDES) is modeled separately, and our approach is described in a later section. To appropriately capture the market for ECTs, we also characterize complementary and competitor technologies and relevant supporting infrastructure not currently modeled in WEPS, including fossil-based hydrogen pathways, hydrogen storage, and carbon capture and storage.

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- Clean technology demand: We modified the end-use modules, including industrial, transport, and building sector modules to allow for greater fuel substitution and clean technology adoption, including hydrogen, electrification, and clean fuels.
- Electric power sector: We revise several electric power sector assumptions that capture the dynamics of high renewable power systems. These include adding greater time slice resolution, relaxing minimum fossil power generation constraints, and revising decay rates for power plants.
- Model timeframe: We extend the time horizon of the WEPS model from 2050 to 2100 to capture a more complete deployment curve of early stage technologies whose market evolution may happen over longer time frames.

**Electric power sector and clean technology supply**

The WEPS international electricity market model (IEMM) 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, now in the future, to inform investment decisions).

The IEMM projects generating capacity (including additions and retirements), generation, fuel consumption, carbon dioxide ($CO_2$) emissions, and prices for the electric power and heat sectors. Rhodium modified the IEMM to include hydrogen production, alternative fuel production (including SAF), and direct air capture. Integrating ECTs into the IEMM'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).

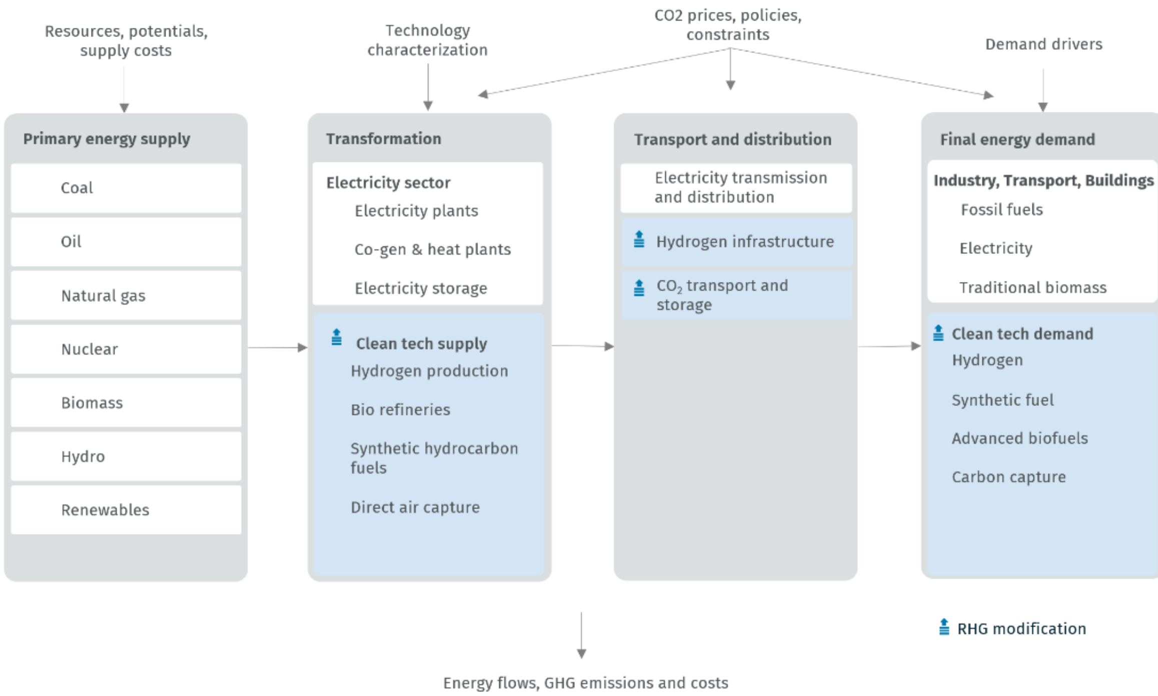
The modified IEMM (henceforth RHG-GEM-IEMM) receives electricity, hydrogen, and sustainable fuel demand, sectoral fuel prices from each end-use module (residential, commercial, industry, and transport), along with captured $CO_2$ from the industrial module. For each of the end-use modules, RHG-GEM-IEMM provides the following projections:

- Biomass, electricity, hydrogen, and alternative fuel wholesale prices
- Electricity retail prices
- Fuel consumption to produce electricity, hydrogen, and alternative fuels

FIGURE 1

**Overview of the RHG-GEM-IEMM energy system**

Rhodium Group modifications are highlighted in blue




Rhodium made the following modifications to the IEMM:

- **Variable renewable power sources:** We made a number of updates to the IEMM to better capture the dynamics of high-penetration renewable electricity systems. This included increasing the annual resolution from 12 to 36 time slices, providing greater seasonal and time-of-day representation in electric load and supply. We also updated or removed a number of constraints that limited renewable deployment, including updating capacity factors on natural gas and coal plants that limited fossil fuel retirements and modifying build rates and grid constraints for renewables. We also updated capital and O&M costs for fossil fuel and renewable technologies to be consistent with the AEO 2022 and NREL's 2022 Annual Technology Baselines, respectively.

- **Hydrogen transport and storage:** 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 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 capture for power plants:** We change relevant cost and performance parameters for power generating facilities equipped with carbon capture technology, 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 CO2-fired power plants.

- **Carbon transport and storage:** Carbon transport and storage costs are extracted from the original WEPS model and are estimated to be 40$/tCO2. We assume annual CO2 injection rates that become less constraining over time as new storage resources are developed and technology improves. For Europe, we limit annual CO2 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

The WEPS approach for industry is designed to model current policy scenarios, using historic fuel consumption and macroeconomic trends to project energy demand for modeled years and applying price elasticities from the World Bank to capture changes in fuel mix. This approach only allows for minimal fuel switching and does not currently include ECT and other clean alternatives. We developed a broadly-applicable approach for projecting industrial fuel demand that enables greater fuel switching, with additional modeling assumptions for key energy-intensive industries, including iron and steel, cement, and chemicals, that allow characterization of specific new technologies.

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. This allowed better characterization of technology and fuel choice based on heat requirements and other real-world limitations. Total demand for the end-use category was projected utilizing a log-log regression on historic fuel demand per unit of economic output and GDP per capita. This regression assumes that as GDP per capita increases, the energy intensity per unit of economic value decreases, with exceptions if there is a strong correlation otherwise.

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:

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

Where s is the share of total demand met by a given fuel, $\alpha$ is a preference parameter calibrated from historic data, $\beta$ is a user defined parameter and p is the fuel price. The $\beta$ 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 $\alpha$ 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 in order 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 which may turnover in a given year. In a given 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.

Iron and steel

A sector-specific stock accounting model was applied in the iron and steel sector, which calculates demand for total steel production and retirements in every year using a regression model similar to other sectors. 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.

Cement

The generic logit model is applied to all fuel usage categories in the cement sector except for fuel used to heat cement 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. 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

In the chemical sector, we focus on ammonia and methanol production, which together account for 38% of global hydrogen demand today and are considered an important opportunity for future clean hydrogen demand.[1] We divided fuel use in the chemicals industry – represented as an aggregated sector in WEPS - into three major sectors, ammonia, methanol, and high-value chemicals (HVCs). 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 subtracted from the chemicals sector, and hydrogen demand is sent to RHG-GEM-IEMM where hydrogen production mix is determined based on a least-cost optimization. Given that urea and methanol require a source of carbon, we assume 50% of hydrogen production for ammonia and 100% of hydrogen production for methanol requires carbon-based hydrogen (including with capture). Remaining fuel usage in the chemicals sector is solved for 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 switching from oil to low-carbon fuel production. The WEPS model projects demand for refining fuel use based on oil product demand and historic refinery gain, but does not explicitly project hydrogen demand for refining. We update the model to project hydrogen supply for refineries based on the historical amount of hydrogen required per unit of refined product. The resulting demand is sent to RHG-GEM-IEMM, 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.

[1] IEA

In addition to adopting clean technology in refineries, demand for traditional oil refining is replaced by biorefining and synthetic fuel production as demand for alternative hydrocarbon fuels grows.

### Transportation

*Light-duty vehicles (LDV)*

WEPS predicts demand for LDVs based on a vintage stock model. Sales shares by vehicle technology type are determined based on relative vehicle price, fuel price, and make-and-model and fuel availability. We assume the cost of EV ownership will achieve parity with internal combustion engines (ICEs) in most markets in the next few years, and that long-run market growth will be driven primarily by non-cost barriers like consumer preferences and infrastructure investments which are not well-characterized in the model. We therefore developed a simple model for country-level LDV electric vehicle (EV) adoption that aims to capture uncertainties in future market share. We assume Norway will continue to be the global leader in LDV electrification, reaching 90% of EV and PHEV sales share by 2050[2]. For all other countries, we determine future sales shares based on current EV share, assuming market growth converges over time with the global leader consistent with convergence in income per capita. We project EV sales share by country (and by state for the US) and calculate the sales-weighted regional average for each of the 16 regions in the RHG-GEM demand modules.

The EIA model captures all national fuel economy standards currently on the books through 2025. Post-2025, we assume ICE fuel economy improves over time due to technological progress and moderate policy action. Annual improvements are based on a moderate improvement scenario from GEFI.

*Two-and three-wheelers*

Fuel consumption of two-and three-wheelers is projected by calculating total vehicle kilometers travel, exogenous fuel shares, and average fuel economy. In our revisions, we calculate exogenous electrification shares by region using historical electric shares and taking China as the lead region. We assume that the rest of the regions will follow China's electrification pathway with certain delays based on their GDP per capita and the relative fuel price difference between motor gasoline and electricity.

*Freight*

Heavy-duty vehicle, rail, and domestic marine fuel consumption is computed by projecting travel demand and energy efficiency. The travel demand (in ton-miles) is projected for nine industrial output commodities (chemicals, iron and steel, food, paper, refinery, non-metallic minerals, agriculture, extraction, and other industries) and aggregate for the total demand. The split among the modes is based on user-defined assumptions.

*Heavy-duty vehicles (HDV)*

HDVs (including passenger buses) are modeled as three modes — light, medium, and heavy trucks. In our revisions, we further split medium and heavy trucks 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.

We assume demand for electrified travel[3] in light, short, medium, and heavy trucks is tied to LDV electrification with a delay of several years. In light trucks, electrification is delayed by 5 years; for short-haul medium and heavy trucks, it is 10 and 15 years, respectively. We assume fuel cell electric vehicles (FCEV) will be more suited for long-haul medium and heavy trucks than electric battery drivetrains due to FCEV's longer range, faster refueling times, and lower risk of lost cargo capacity. The share of total demand for freight travel in ton-miles met by FCEVs and their ICE alternatives is determined using a logit choice model based on cost per mile, including hydrogen delivery

[2] We assume some share of vehicles will be unable to electrify; for example, due to infrastructure constraints in certain geographies.
[3] LDV travel demand is measured in vehicle miles travelled (VMT) and HDV travel is measured in ton-miles.

and refueling cost. As a proxy for stock turnover, the switch from ICE to FCEV is limited using annual turnover rates based on the typical lifespan of vehicles.

Further, we assume moderate ICE fuel economy improvements for trucks through 2050, based on a "moderately aggressive" scenario from the Global Fuel Economy Initiative's (GEFI) analysis of technically feasible fuel efficiency targets and Rhodium expert judgment.

*Marine*

We introduce ICE hydrogen and ICE ammonia technology and liquefied natural gas (LNG) fuel for domestic and international marine fuel consumption. The future share of fuels in marine consumption is determined using a logit model based on the total cost of ownership of different powertrains in shipping. The total cost of ownership is calculated based on IEA assumptions for base ship cost, fuel cell/engine cost, fuel storage, infrastructure and delivery costs.

*Aviation*

The EIA model projects the air travel demand for domestic and international aviation using an econometric model based on GDP and population. When extended through 2100, this model yields air travel demands significantly higher than other leading sources. Therefore, to project demand through 2100, we apply growth rates consistent with recent air travel demand projections from Shell Energy and the IEA's Sustainable Development Scenario. In our revisions, we also allow drop-in sustainable aviation fuel to compete with traditional aviation fuels. The future shares of each fuel are determined by a logit choice function based on projected fuel prices.

**Buildings**

WEPS residential and commercial energy demands by fuel are calculated based on a simple index of the projected changes in household or commercial services income, changes in fuel prices, and a long-term trend. As such, there is little opportunity for fuel substitution. We updated the building modules to allow for greater fuel options and efficiency improvements. 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.

$$demand_t = demand_{t-1} * (driver_t / driver_{t-1})^{elasticity}$$

The table below shows each energy service demand and the corresponding driver:

| Energy service demand | Socioeconomic driver |
|---|---|
| Cooking, hot water | Population |
| Space heating, space cooling, refrigeration, clothes washing/drying, dishwashing, | Number of households (advanced economies), GDP/household (developing economies) |
| Lighting, other demands | GDP/capita (advanced economies), GDP/household (developing economies) |

Historical energy consumption by energy service is calibrated to data from the TIMES Integrated Assessment Model (TIAM). For each service demand, region and year, fuel switching potentials are developed based on data from BNEF's 2019 New Energy Outlook and IEA's Sustainable Development Scenario. Fuel switching, triggered by fuel prices generated by RHG-GEM-IEMM, is used to calculate fuel consumption by end-use.

## Emerging Climate Technology Baselines

### Technology assumptions

*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, and power to liquids/gas. All demands except hydrogen used for fuel production are exogenous to RHG-GEM-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*

We characterize DAC in RHG-GEM-IEMM based on the liquid sorbent approach. We assume heat for the process can be produced on-site or off-site.

### ECT cost and performance

We established 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.

As these technologies scale, future costs are expected to come down. To capture this price decrease, we determined learning rates—the cost reduction for each doubling of deployment—for each technology. For many ECTs, technology learning rates are difficult to estimate empirically due to the lack of historical deployment experience and data. Technology learning rates are therefore based on the best-available academic research, input from industry experts, and technological maturity. We take into account that certain cost components may have different limits on learning potential. For example, a technology's efficiency might be unlikely to improve beyond a certain rate or the operating costs have a price floor. Additionally, we use a high and low learning rate for each technology to capture uncertainty in the values.

TABLE 1
**ECT current cost assumptions**

| | Technology | CAPEX | | Fixed O&M | | LCOE | | Learning rate | |
|---|---|---|---|---|---|---|---|---|---|
| | | Unit | Cost | Unit | Cost | Unit | Cost | Low | High |
| Hydrogen | Biomass gasification + CCS | $/kW | 3,324 | $/kW | 96 | $/kg | 5 | 10% | 20% |
| | Methane pyrolysis | $/kW | 5,983 | $/kW | 172 | $/kg | 3.2 | 10% | 20% |
| | PEM electrolysis | $/kW | 1,200 | $/kW | 36 | $/kg | 3.2 | 10% | 20% |
| | SMR + CCS | $/kW | 1,680 | $/kW | 84 | $/kg | 2.1 | 5% | 15% |
| DAC | DAC on-site steam | k$/ton | 7.50 | | 0.04 | k$/ton | 510 | 10% | 25% |
| | DAC off-site steam | k$/ton | 6.80 | | 0.04 | k$/ton | 420 | 10% | 25% |
| SAF | HEFA | $/kW | 2,510 | $/kW | 0.6 | $/gl | 2.8 | 5% | 15% |
| | Biomass Fischer-Tropsch + CCS | $/kW | 4369 | $/kW | 132 | $/gl | 5.3 | 5% | 15% |
| | Power-to-liquid Fischer Tropsch | $/kW | 2,036 | $/kW | 29 | $/gl | 4.4 | 10% | 20% |

Electrolysis, DAC, and power to liquids Fischer-Tropsch costs performance parameters are based on Rhodium analysis. Costs for hydrogen facilities equipped with carbon capture, methane pyrolysis, bio-based fuels, and HEFA are based on Evolved Energy Research's data. DAC is based on a liquid sorbent technology.

## Long Duration Energy Storage (LDES) modeling

RHG-GEM in its current form isn't well suited to capture the granularities of the long duration energy storage market, including distinguishing between short and long-duration batteries (e.g. 4 and 8+ hour storage). We therefore model LDES separately from RHG-GEM, but in a way that's consistent with its outputs. LDES technologies shift intermittent electricity generation from periods of excess supply to periods of low output. This resource is intended to enable higher penetrations of renewable energy and to replace natural gas peaker plants. However, LDES faces two major barriers to scale-up. The first is competition from technologies like electrolysis that can serve as flexible load and make productive use of excess renewables. The second challenge comes from natural gas-powered peaking plants. Unless natural gas is explicitly banned, LDES will likely have a hard time competing with gas peakers plus $CO_2$ removal offsets in a decarbonized system.

Given these challenges, LDES is likely to deploy only in regions with supportive policy, such as a ban on natural gas peaking generation or an 100% renewable electricity goal. To construct our deployment baselines, we define a high and low scenario for uptake of these policies. In our upper bound, all US states plus the EU27, Norway, UK, and Iceland adopt a ban on natural gas peakers. In the lower bound, this is limited to US states and European countries with net-zero commitments. We then estimate a total flexibility need, defined as the largest diurnal difference between base and peak load in our RHG-GEM-IEMM modeling results. These results already capture the flexible demand response of hydrogen-based fuel production and the role of 4-hour battery storage in shifting demand. However, we additionally assume a share of the flexibility need can be met by flexible demand resources, which are not implicitly modeled. We assume the remaining need is met by LDES.

### Sources of uncertainty

Given the current degree of uncertainty in global energy markets, technology, and consumer behavior, it's important to understand the global energy system outlook under a range of uncertain future conditions. We parameterize four key sources of uncertainty:

- ECT 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 each ECT, we consider a high and a low learning rate – defined as the cost reduction for each doubling of deployment - to reflect uncertainty in future cost reductions.

- Oil and gas markets: We consider a range of global oil and natural gas prices that will shape the competitiveness of fossil technologies relative to cleaner alternatives.

- Renewable technology cost and performance: Low-cost, clean electricity is an important enabler of many low-carbon technologies. We estimate ranges for key renewable technology cost and performance variables, including capital and operating costs for solar, wind, and utility-scale storage.

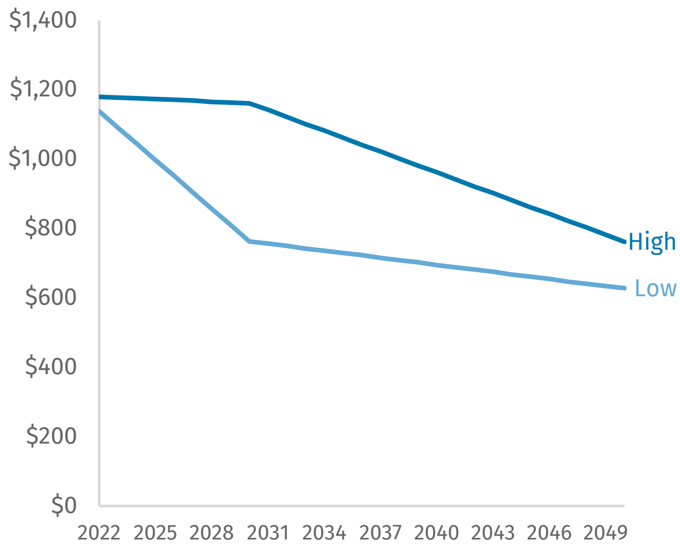
Below we characterize the energy market assumptions that vary across our estimated ECT deployment ranges and underlying data sources. For each parameter, we defined a low and high case to reflect a range of energy market, technology cost, and behavioral uncertainties. These assumptions are coupled with uncertainty in ECT learning rates described above to construct the full range of deployment projections for each technology pathway. We focus our discussion below on the US market and provide descriptions of regional differences.

Renewable technology costs: We assume capital costs for utility-scale solar photovoltaic, land-based and off-shore wind, and utility scale energy storage decline according to NREL's 2022 Annual Technology Baseline's (ATB) technology cost projections. Our low- and high-cost assumptions follow the Moderate Technology Innovation Scenario and Conservative Scenario, respectively.

FIGURE 2

**Utility-scale solar photovoltaic overnight capital costs**

2021 dollars per kilowatt

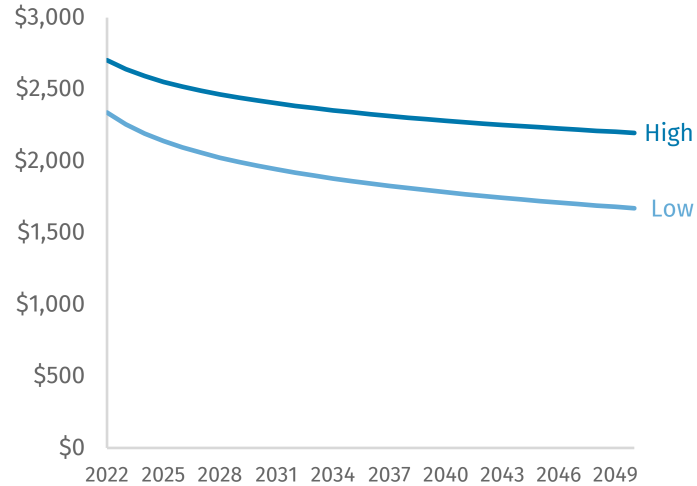



Source: Rhodium Group analysis, NREL, EIA

FIGURE 3

**Offshore wind overnight capital costs**

2021 dollars per kilowatt

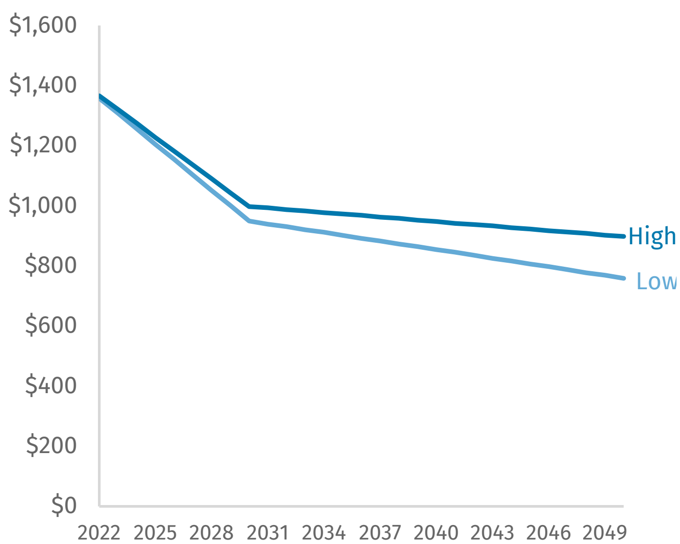



Source: Rhodium Group analysis, NREL, EIA

FIGURE 4

**Land-based wind overnight capital costs**

2021 dollars per kilowatt

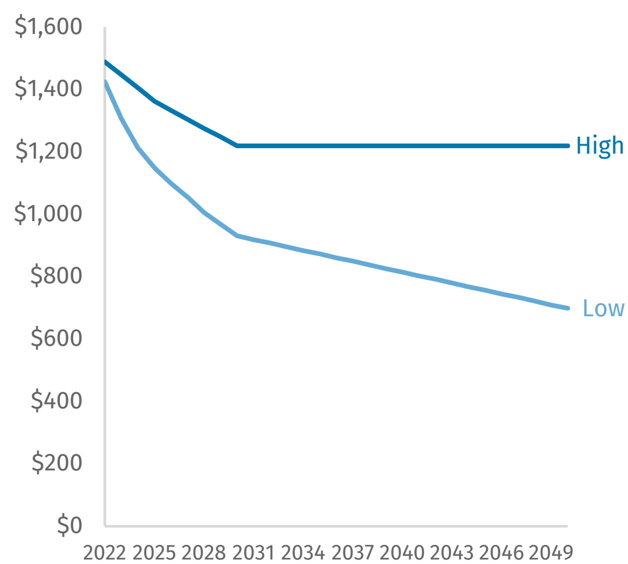



Source: Rhodium Group analysis, NREL, EIA

FIGURE 3

**Utility scale 4-hour battery energy storage overnight capital costs**

2021 dollars per kilowatt




Source: Rhodium Group analysis, NREL, EIA

Natural gas and oil resource and prices: In RHG-GEM, oil and natural gas production is assumed to scale up or down from a global baseline to meet the projected level of aggregate demand. Baseline natural gas and oil prices are updated by applying a price elasticity of supply to the delta in production. We update WEPS baseline oil price and global supply assumptions to be consistent with EIA's Annual Energy Outlook 2022 long-term projections. For gas, the AEO projects only US prices and supply - not global. We therefore use projected global supply from IEA's 2021 World Energy Outlook (WEO) Stated Policy Scenario, and then for each WEPS region, scale natural gas prices to AEO2022 US prices based on its historical cost differential with the US. For our low cost baseline, we use the oil and natural gas prices reflected in the AEO2022 reference case. In this case, natural gas averages $3.50/MMBtu through 2050 at Henry Hub, and Brent crude rises from $65/barrel in 2024 to $80/barrel in 2050. In our high cost baseline, we use the oil and natural gas prices reflected in EIA's low oil and gas supply side case. Henry Hub natural gas prices in our high cost case average $5.74/MMBtu through 2050, while Brent crude rises to $104/barrel in 2050.

To determine regional allocation of production, we use the WEO 2021 scenarios – State Policies, Announced Pledges, and Sustainable Development – which provide a range of country-level oil and natural gas production outcomes at different levels of global demand. We use these projections to estimate a national share of global supply that varies by global production level, which we apply to aggregate demand from all end-uses to find regional production.

**Policy Assumptions**

To capture how policy is likely to incentivize ECT deployment, we must make some assumptions about how policy will evolve over time. Rather than attempt to predict prescriptive, policy-specific developments over the course of the next few decades for each region of the world, we use a proxy for policy that ties to a well-understood metric used by the US government to measure the rising cost of climate to the economy over time. For each scenario we apply an escalating carbon price that aligns with the Social Cost of Carbon (SCC) adopted by the Biden administration in 2021. To provide differentiation among regions and countries with varying degrees of climate policy ambition, we scale the US SCC based on regional income per capita relative to the US. The one exception is for Europe, where we assume the carbon price starts at the average EU ETS allowance price in 2022, and grows at the pace of the US SCC. The SCC rises over time so eventually all ECTs deploy, just not soon enough to meet global temperature targets.

Because the green premium for ECTs remains high over the next few decades, policy that follows a price path similar to the SCC is insufficient to spur significant ECT deployment. As we have seen in the US with the Inflation Reduction Act and the EU's Green New Deal, we do expect direct subsidies and other policies that specifically target ECT deployment to go above and beyond what a simple carbon price will achieve in terms of expected ECT deployment. We therefore incorporate all relevant ECT-specific policies adopted as of September 2022 in addition to our SCC-aligned carbon price.

## Disclosure Appendix