Methodological Appendix

Version: 1.0 (February 3rd, 2025)

This is the methodological appendix to "**All In: Strategies for Climate Philanthropists in a New Political Landscape**".

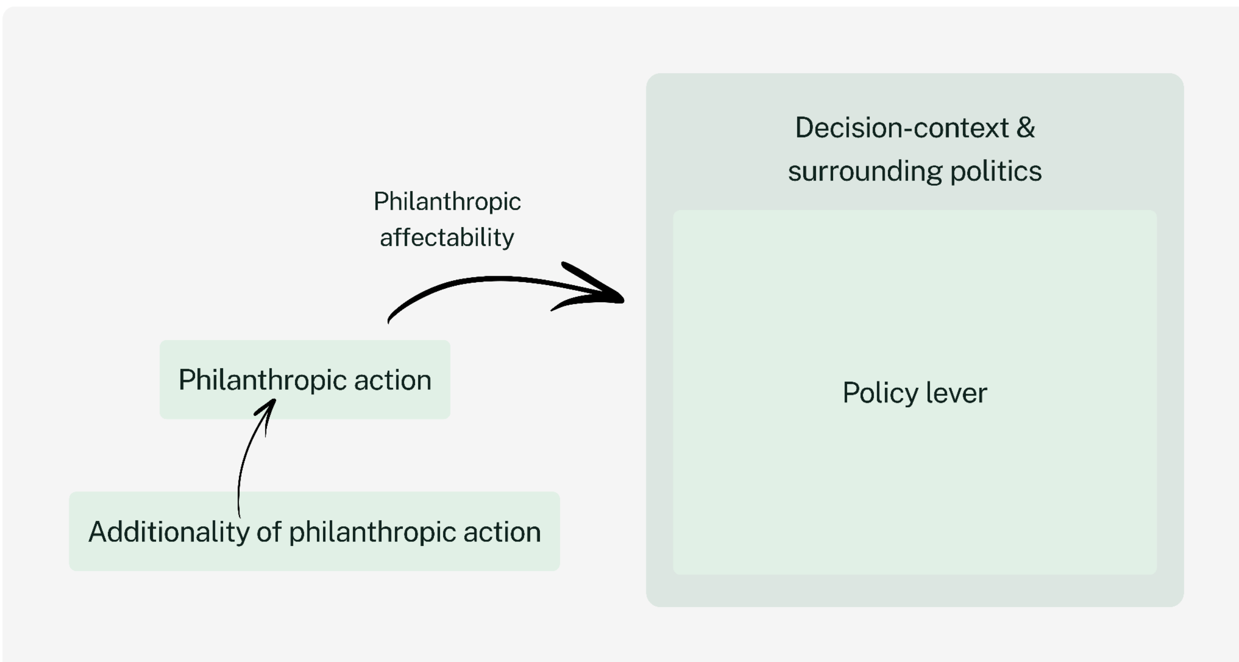
We have tried our best to document our process and assumptions transparently. If you have further questions, do not hesitate to reach out.

For general questions on the report, please contact johannes@founderspledge.com. For questions on this methodological appendix specifically, please contact stan@foundersplege.com.

The philanthropic prioritization model

We begin by laying out a framework for how philanthropists can decide which **policy levers warrant further engagement, keeping in mind what's already being done by other philanthropists.**

Figure 1. How philanthropy affects policy levers
Source: Founders Pledge



To make sense of the complex landscape of philanthropic strategies for engaging with policy levers, we've developed a model for philanthropic prioritization. Our model considers three key dimensions: **importance**, **affectability**, and **additionality**.

For any given policy we might choose to engage with, we need to look at that policy's *importance*: **What is at stake for the climate if this policy decision goes one way versus the other?** Other factors held equal, we should spend our resources on policies that will have a significant impact on climate outcomes, rather than ones that are unlikely to make a difference.

We also need to consider a policy lever's *affectability*: **How much leverage do philanthropists have in changing the policy outcome?**

This breaks down into two components:

Swayability: A policy that will almost certainly be enacted or overturned is — everything else being equal — a lot less affectable than a policy that still seems like it could swing either way, and we shouldn't waste resources trying to change outcomes that are already set in stone.

Philanthropic affectability: Separately, we also need to consider *why* a policy decision might swing either way. If the decision is close because it depends on factors outside of philanthropic control, such as geopolitical influences, then that issue is likely not the best place for philanthropists to spend our resources.

Finally, we need to look at *additionality*: **how much additional value would our efforts add, considering the existing attention and resources already devoted to the issue**? Put more simply: how likely is it that our desired outcome would already happen even without our funding? We need to make sure our philanthropic resources make a difference on the margin, which might mean deprioritizing highly important and affectable issues that are already receiving sufficient attention from other funders. **Spaces that are neglected by other funders are often the most likely to have opportunities for high additional impact, all else being equal**.

This systematic approach helps ensure we **direct resources where they can have the greatest impact** and can serve as useful philanthropic leverage points**, rather than simply following conventional wisdom about which policies are important or public salience**. This is particularly crucial in the current political environment, where we must carefully choose where to focus our efforts for maximum effect.

Formalizing the model

The Philanthropic Prioritization model estimates the expected marginal impacts of climate philanthropists focusing on each policy lever. The model calculates the product of four variables:

- Importance: The emissions effects of the policy lever, in Gt CO_2e
- Swayability: The degree to which the policy outcome is a "close call": The more 50:50 the outcome, the more swayable the outcome is. Swayability is scored on a 0-1 scale, and is inferred from the probability of the policy outcome happening anyway.
- Philanthropic Affectability: The degree to which philanthropists can affect the policy lever, on a 0-1 scale.[1]

[1] This is a way of capturing the *relative* affectability of policies: a score of 1 does not mean absolute confidence in affecting the outcome.

- Funding Additionality: The degree to which additional philanthropic funding on affecting this policy lever would be truly additional, and not merely displacing other funding.

This calculation was implemented using a Monte Carlo simulation on Python with 10,000 samples. Each of the above four variables was sampled from a distribution, and each distribution was generated from a low and high input. More information on this is provided in the next sub-section.

Converting inputs into distributions

For each input type we use a low and a high estimate. These were converted into distributions as follows:

- For Importance: the distribution is a normal / lognormal distribution with the low and high estimates as 5th and 95th percentiles. We use whichever of normal / lognormal is a better match for our low/mid/high estimates
    - For a small minority of estimates, the low/mid/high estimates were nearly symmetric (evenly spaced) and the low estimate was negative or a very low positive number. A normal distribution is suitable in these cases because:
        - It is symmetric, even when the ratio between 5th and 95th percentiles is very high
        - It can be negative
    - In other cases, a lognormal distribution was used. This is suitable because:
        - The data shows a positive skew. For all cases in which we use a lognormal distribution, the geometric mean of the 5th and 95th percentiles (which is the median of a lognormal distribution) is a better approximation of the "mid" estimate than the arithmetic mean of those percentiles (which would be the median of a normal distribution.
        - Uncertainty about emissions effects is likely to be the *product* of multiple uncertain variables (such as energy prices, policy persistence and emissions intensity), and not the *sum* of uncertain variables. By the multiplicative Central Limit Theorem, lognormal is the appropriate choice here.
- For all other inputs (Affectability, Probability and Additionality), the low and high estimates are converted into odds, and form the 5th and 95th percentiles of a lognormal distribution of odds[2]. After sampling, these odds are converted back into proportions. This process ensures that:
    - The low and high estimates are 5th and 95th percentiles of the distribution
    - Affectability, Probability and Additionality are bounded by 0 and 1

[2] To prevent the model breaking when values equal to or very close to zero or one are used, we enforce bounds of 0.01 and 0.99 on 5th and 95th percentiles.

- The distribution is more similar to the Beta distribution - widely accepted as a good model for proportions - than it is to the normal distribution. The Beta distribution may have been a preferable choice here, but inferring alpha and beta parameters from percentiles is too computationally expensive for use in a Monte Carlo simulation

Probability of happening anyway, and how we convert this to swayability

Amongst the four variables entering our prioritization model, three are entered directly and estimated as discussed above.

The fourth, swayability, is derived from the probability of the policy changing, our estimate of the degree to which the policy lever is affectable to "switch" in one or the other in general. The structure and logic of this process is discussed here, A discussion of those probabilities chosen is provided below in the corresponding "Specifying the Model" section.

For each policy lever, we defined lower and upper bound probabilities of policy change happening. These low and high estimates were used to form a distribution of probabilities using the method described above.

Swayability

While there are plenty of estimates in the expert literature on the emissions relevance of different policy levers, what ultimately matters for prioritization of taking action is not only the impact of the policy lever if "switched" but also how likely it is to be switched.

We call this property *swayability*. Clearly, if a policy outcome has a 100% chance of happening anyway, its swayability is zero. If its probability of occurring is 99% (or, equivalently, 1%), unusual conditions are required to change the outcome, and its swayability is low. Since a policy *occurring* or *not occuring* are both policy outcomes, we should expect swayability to be symmetric. That is, policy outcomes with probabilities 90% and 10% of occuring are equally swayable. It follows that a policy with probability 50% is maximally swayable.

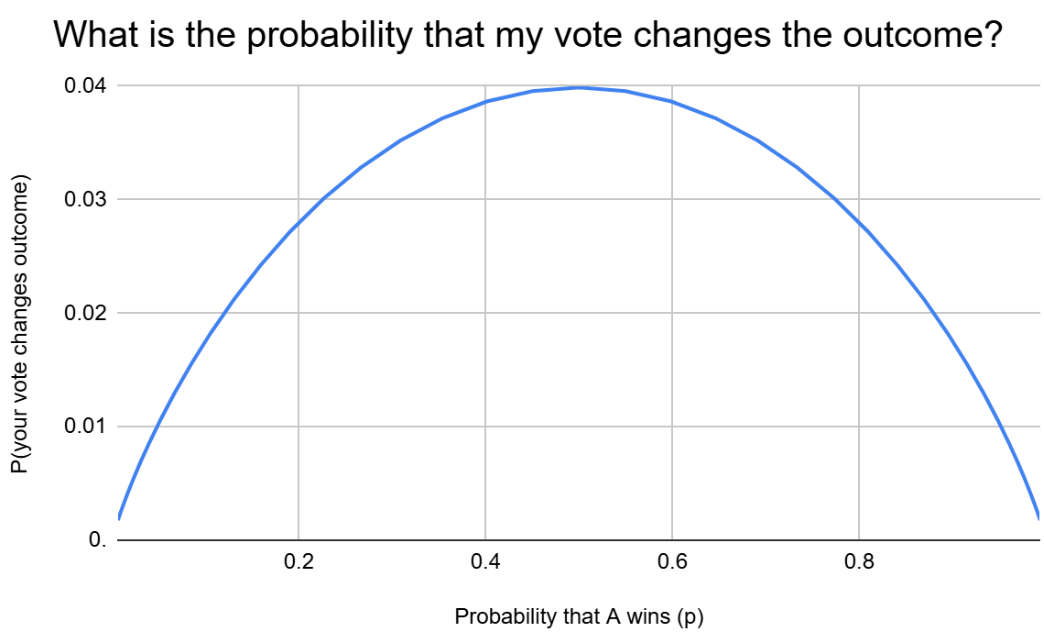
Note that this discussion is about a policy in general and not specific to whether or not it can be affected philanthropically (which is why "philanthropic affectability" is a separate variable in our model). Policies might be very swayable and yet not be priority targets for philanthropic action, for example when their outcome depends mostly on factors outside philanthropists' control.

To determine the transformation required to convert *probability* into *swayability*, we used the **intuition pump** of *deciding vote in an election*: Given that party A has probability **p** of winning the election (according to opinion polls, say), what is the probability that my vote for party A changes the outcome? The probability that I have the deciding vote is maximized when **p** = 0.5, and approaches zero when x approaches zero.

This is similar to what we care about because:

- Just like before an election, we are unsure about policy outcomes yet we have some indication of how likely they are
- Philanthropic action can be thought of as like an additional vote in an election: it increases the probability of success only incrementally, and is more likely to change the outcome in contests that are "on the fence"

We modeled party A's vote share as a Beta-distributed random variable[3] Y with probability **p** of being over 0.5 (P(Y > 0.5) = **p**), and my vote as an incremental increase in vote share of 0.001. This allows us to observe the probability that my vote changes the outcome, and we can see how this probability changes as **p** varies.[4]



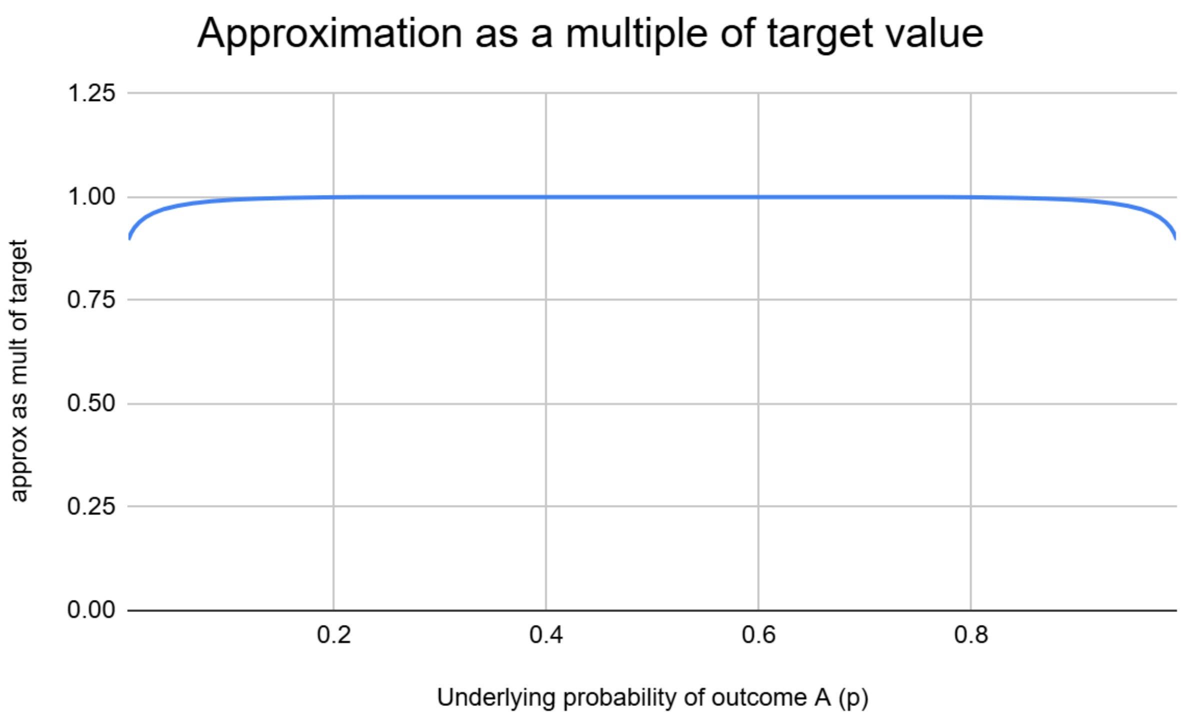
The equation of this chart involves using the inverse Beta distribution, which is not practical in a Monte Carlo Simulation. So we found another equation that approximates it well:

[3] We replicated this approach with normally-distributed uncertainty and found that it led to an identical-looking curve.

[4] When we vary the SD of the Beta distribution, or the size of the increment represented by one vote, the probability of my vote changing the outcome changes. However, the *shape* of the curve does not change as long as the increment is sufficiently small.

$$y = \frac{kp(1-p)}{0.56-\sqrt{0.1936-0.7744(p-0.5)^2}}$$

Where **y** is the probability of my vote changing the outcome, **p** is the probability of party A winning, and **k** is a constant. To examine the error we introduce with this approximation, we can express the approximated value as a multiple of the target value:



We see that for values of **p** between 0.1 and 0.9, we have a very close approximation, with errors of up to 10% for extreme values of **p**.

To convert *probability* to *swayability,* we use the formula below, with **k** set to 25.1 so that the maximum swayability value is 1, when probability is 0.5.

$$y = \frac{kp(1-p)}{0.56-\sqrt{0.1936-0.7744(p-0.5)^2}}$$

Note that we treat this as an intuition pump and we are not arguing that our metric of swayability is an expression of an electoral dynamic.

Specifying the model

Having laid out the model structure, we now discuss how we estimated parameter values.

Policy Levers

Based on following the conversation, we selected the list of policy levers featured by their emissions relevance and salience.

While we believe we chose the most salient issues, we would hope to include further policy levers in a future edition if they become relevant.

Issues that we would hope to include in a future version are (a) tariffs, (b) border-carbon adjustment and (c) implications of DOI on federal lands for renewables.

General approach

We conducted extensive research into the policy levers that will be relevant under the incoming administration. We analyzed hundreds of published sources, conducted interviews with policy experts, and synthesized dozens of research studies on the emissions effects of potential policy changes.

We also made the following methodological choices:

- (1) Always **include and represent uncertainty**: This follows directly from our general methodological commitments.

- (2) Make estimates **as comparable as possible** by applying consistent adjustments. To choose the most obvious example, many estimates apply different time frames, which makes this incomparable without annualization. We applied this and other adjustments to make estimates comparable.

- (3) Making estimates **as informative as possible** by deriving key quantities of interest. Often, estimates are expressed as units that are intermediate inputs with regards to our key quantity of interest, changes in expected emissions. In those cases, further steps are necessary to make estimates informative with regards to this study. The most typical example of this adjustment is translating estimates in changed capacity into emissions changes.

Typical steps to make estimates comparable, infer key quantities of interests, and extrapolate.

Throughout this study, we sought to apply consistent standards in making our estimates comparable, in inferring key quantities of interest (e.g. translating capacity changes to emissions changes), and in extrapolating in the face of partial data.

The below sections explain the logic and provide examples of those typical adjustment steps.

Converting one-year effects into year-by-year or cumulative effects

Our sources often estimate effects only in select years, eg. 2030 and 2035. When we convert these into year-by-year effects, we usually assume that:

- Effects (that is, differences between policy scenarios) start from zero in 2025
- Effects change linearly between data points. For example, if emissions effects increase from zero in 2025 to 500Mt in 2030 and 550 Mt in 2035, the year-by-year effects would be as follows:
    - **2025: 0 Mt**
    - 2026: 100 Mt
    - 2027: 200 Mt
    - 2028: 300 Mt
    - 2029: 400 Mt
    - **2030: 500 Mt**
    - 2031: 510 Mt
    - 2032: 520 Mt
    - 2033: 530 Mt
    - 2034: 540 Mt
    - **2035: 550 Mt**
- We apply the above rule to whatever is estimated by the source, eg. capacity or emissions.

Converting capacity to generation

We apply this approach when a given estimate provides capacity, but not generation.

REPEAT's [Climate Progress 2024 report] gives estimates of US electricity capacity and generation by source under two policy scenarios, Current Policy and Frozen Policy. Frozen Policies represents pre-IRA climate policies of the beginning of Biden's term in January 2021.

For various sources of electricity generation, the report shows:

- Capacity in 2024 and 2035 under each policy scenario
- Generation in 2024 and 2035 under each policy scenario

This allows us to infer the electricity generated in 2024 and 2035 by each GW of capacity, for each energy source. We use the average of the Current Policy estimates from 2024 and 2035.

Generation per unit capacity (Twh / GW-year)			
Source	**2024**	**2035**	**Average**
Wind	3.19	3.59	3.32
Solar	1.87	2.10	1.95

Applying this approach is motivated by two key factors:
(1) Consistency of approach (see above); (2) We believe that the REPEAT scenario outlines a good estimate of expected generation changes given broader energy system changes. In other words, rather than relying on a theoretical estimate of capacity factor for new resources, we believe that deriving these estimates from a model that includes factors such as (i) changes in capacity factor due to adding new resources in specific localities and (ii) broader changes in the energy system, is a better approach than, for example, relying on current capacity factors. We see the REPEAT estimate as an approach to estimate the average capacity factor across marginal additions over this period.

Converting generation to averted emissions

When direct estimates of emissions reductions aren't available, we need a method to convert clean energy deployment into emissions impact. Our approach leverages the relationship between increased clean power generation and decreased fossil fuel emissions, as modeled in [REPEAT's Climate Progress 2024 report].

The report shows that the Biden-era climate policy (most notably the IRA) causes an increase in clean energy generation and a decrease in coal and gas generation. Since the IRA incentivizes clean energy generation but does not disincentivize coal and gas generation, we think it is reasonable to assume that any reduction in coal and gas generation due to the IRA occurs because of increased competition from clean energy. We assume that smaller increased in clean energy generation would displace coal and gas generation in the same way.

We assume a relationship between capacity, generation, and emissions works as follows:

- New clean energy capacity leads to increased clean power generation

- This additional clean generation displaces existing fossil fuel generation from coal and gas plants
- Reduced fossil fuel generation directly leads to lower emissions, based on the emissions intensity of the displaced sources

We use REPEAT's modeling of the IRA's impacts to quantify these relationships. REPEAT compares two scenarios: Current Policies (with IRA) and Frozen Policies (pre-IRA baseline from January 2021). By examining how clean energy deployment under the IRA affects the generation mix and resulting emissions, we can estimate the emissions impact per unit of additional clean energy generation.

While REPEAT only provides estimates for 2024 and 2035, we assume linear growth in the difference in generation between scenarios over this period. This simplifying assumption allows us to estimate cumulative impacts, though it may not capture year-to-year variations in deployment rates or grid conditions.

The analysis suggests that over 2025-35, the IRA drives an additional 10,932 TWh of clean power generation while reducing emissions by 2,115 Mt CO2e through decreased fossil generation[5]. This yields an emissions displacement factor of 0.193 Mt CO2e per TWh of clean generation.

This methodology has several strengths and limitations:

- We do not rely on theoretical assumptions about the extent to which renewables displace fossil fuel generation
- The ratio-based approach is relatively robust to uncertainty in the absolute magnitude of IRA impacts, as both generation and emissions estimates would likely be affected proportionally
- However, it assumes the marginal displacement pattern remains consistent at smaller scales, which may not hold if local conditions differ significantly
- Linear interpolation between 2024 and 2035 may oversimplify the actual deployment trajectory

This approach allows us to draw upon studies that do not model emissions effects. We believe that although our approach introduces additional assumptions, the benefits of widening our evidence base outweigh the risks of additional assumptions.

[5] 977 Mt CO2e from 930 TWh less coal at 1.05 Mt/KWh, and 1,139 Mt CO2e from 2,561 TWh less gas at 0.44 Mt/KWh. We use EIA estimates of the emissions intensities of coal and gas generation.

Accounting for Policy Persistence

Policy can be reversed. The likelihood of this happening depends on the type of policy (see our discussion of the features of different policies / regulations in the main report). We model the below probabilities of reversal every four-year term:

- Regulations (can be enacted unilaterally by administration): **50%**;
  - this estimate is based on the observed past of partisan changes and attendant repeal of executive orders in this area

- Policy requiring simple majority: **50%**
  - This estimate is based on the observed changes in funding priorities

- Policy requiring 60% majority: **10%**
  - This estimate is based on the fact that policies passed on filibuster-proof majorities rarely get repealed.

These estimates are not meant as precise probabilities, but rather as broad stylized facts that are correct enough that they improve the comparability of estimates compared to a misleading situation where all policy changes are, effectively, treated as equally likely to be durable.

We treat a policy repeal as a policy in itself. So if an IRA tax credit is repealed in 2025, it has a 50% chance of being reinstated (ie. reversed) in 2029.

These probabilities compound over time. If the probability of the policy being reversed / repealed at the start of the next term in 2029 is 50%, then the probability of it surviving beyond the start of the *term after that* in 2033 is 50%*50% = **25%.**

We do think this approach is sometimes a significant simplification. In particular, if a policy does not get repealed in the next two administrations, it seems likely that it has become the "law of the land", not having an equal probability of being repealed going forward. This would support a model in which the probability of a policy change surviving each four-year term would increase over time.

We apply this approach in our [LNG Export Permits] modeling, but elsewhere we simply apply the same persistence probability every four years.

We checked the effect of this simplification by exploring the effects of alternative persistence assumptions on some of our models. The largest difference we observed was with the [EV model]: under the alternative assumption "if IRA EV repeal survives two four year terms, it survives through 2050", we see the "high" emissions estimate increase by 13%[6]. We conclude that although our persistence assumptions are simplified, they usually lead to underestimating the emissions effects by less than 10%.

Calculating the effect of policy persistence is not simple. Climate policies generally change counterfactual clean energy **capacity** over time. If a policy is reversed after 4 years, **the difference in capacity will continue to affect counterfactual emissions**.

As an intuition pump: if IRA EV incentives are repealed in 2024 and reinstated in 2029, **there will still be fewer EVs on the road in 2029** compared to if the incentives had never been repealed. So transport emissions after 2029 will still be higher than they would have been.

Let's see what this looks like in practice. From the data below on cumulative wind capacity lost due to the IRA we can infer that while the IRA is repealed, 16 GW of wind capacity is not built each year that otherwise would have been built. By 2029 there is only a 50% probability that the IRA remains repealed, and thus the *expected* annual loss in wind capacity falls to 8GW. The persistence-adjusted cumulative loss of wind capacity is simply the sum of expected annual loss of capacity in all previous years. This means that, if we account for the fact that a repeal of the IRA could be repealed, the expected cumulative loss in wind capacity by 2035 is 106GW, which is lower than the initial, "naive" estimate of 173 GW.

[6] The "mid" estimate increases by 1% and the "low" estimate does not change.

Year	Probability of policy persisting	Cumulative wind capacity lost due to IRA repeal	Wind capacity lost due to IRA repeal	Persistence prob * wind capacity lost	***Persistence- adjusted cumulative wind capacity lost:*** ***Cumulative*** **persistence prob * wind capacity lost**
2024		0			0
2025	1	-16	-16	-16	-16
2026	1	-31	-16	-16	-31
2027	1	-47	-16	-16	-47
2028	1	-63	-16	-16	-63
2029	0.5	-79	-16	-8	-71
2030	0.5	-94	-16	-8	-79
2031	0.5	-110	-16	-8	-87
2032	0.5	-126	-16	-8	-94
2033	0.25	-142	-16	-4	-98
2034	0.25	-157	-16	-4	-102
2035	0.25	-173	-16	-4	-106

Once we have this data, we can convert lost capacity into additional emissions.

Sometimes we are not working with capacity - the units we are given are emissions. Remember that if a policy such as EV tax credit repeal is reversed in 2029, there will still be fewer EVs on the road than there would have been, and hence there will still be more vehicle emissions each year after 2029. We assume that in this situation, the annual emissions effects would stay constant after the policy is reversed.

This means that in years when the probability of policy persistence is x%, the year-on-year expected increase in annual emissions effects should be x% of the full policy effect.

In the example table below, we

1. List the year-by-year emissions effects (analogous to differences in clean energy generation)
2. Calculate the increase/decrease in these emissions effects each year **(C)** (analogous to differences in clean energy capacity additions)
3. Multiply this by the probability of policy persistence **(P*C)**
    - For example, if the emissions effects increase from 200MT in 2030 to 240MT in 2031, the emissions effects increased by 40MT. If the prob of policy

persistence is 50%, there is a 50% chance that the emissions effects increase by 40MT between 2030 and 203. 50%*40MT = 20MT expected increase

  - This 40MT change can be thought of as a *change in capacity*: if we add new clean energy capacity, emissions fall by 40MT this year and every year after.

4. Next year's emissions = last years emissions + value calculated at step 3

Example below:

Year	**(P) Probability of policy persistence**	**Naive emissions effect**	**(C) Change in emissions effect since last year**	**P * C**	**Emissions effect accounting for policy persistence: Cumulative P * C**
2025	1	0			0
2026	1	0.06	0.06	0.06	0.06
2027	1	0.12	0.06	0.06	0.12
2028	1	0.18	0.06	0.06	0.18
2029	0.9	0.24	0.06	0.054	0.23
2030	0.9	0.3	0.06	0.054	0.29
2031	0.9	0.34	0.04	0.036	0.32
2032	0.9	0.38	0.04	0.036	0.36
2033	0.81	0.42	0.04	0.0324	0.39
2034	0.81	0.46	0.04	0.0324	0.42
2035	0.81	0.5	0.04	0.0324	0.46
Total		**3.00**			**2.84**

Documentation of specific calculations

We now discuss particularities of specific estimates.

Unleashing Fossil Fuels

EPA Rollbacks

We assume the effects of EPA rollbacks to be the difference between the Rhodium IRA repeal scenario and EPA Rollbacks & IRA repeal scenario. Then we convert 2030 and 2035 emissions estimates into year-by-year emissions estimates for 2025-35, assuming that emissions effects changed linearly between 2025 and 2030 and between 2030 and 2035. This allows us to adjust for policy persistence.

We expect there to be more uncertainty than is captured by the in-model variation from the Rhodium data, so we calculate the standard deviation of the low/mid/high estimates derived from Rhodium, and set our best guess low/high estimates at *mid +/- 2*SD*.

LNG Export Permits

Estimates were taken from table 6 of the DOE report, which shows estimates of net LNG emissions effects under different assumptions. Of the estimates in the table, the lowest nonzero estimate became our low estimate, the median became our mid estimate and the highest became our high estimate.

Policy persistence was accounted for in a slightly different way: the probability of persisting through the first term was 50%, and then 80% for every four-year term thereafter. This reflects the fact that although permits can be frozen unilaterally by the president, the longer LNG exports continue, the less likely it becomes that they are reversed.

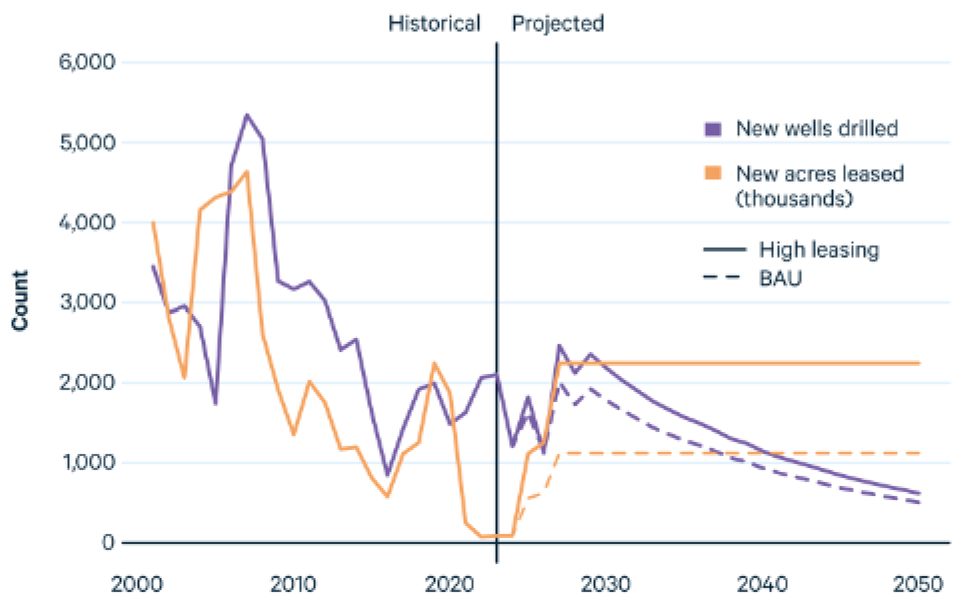
Expanding oil and gas leasing

The RFF report gives the emissions effects of onshore drilling when federal leasing is significantly expanded. We adapt this estimate to account for both onshore and offshore effects by inferring the scale of offshore drilling in comparison to onshore drilling on federal lands:

- According to RFF:
    - 12% of US oil production and 11% of US gas production is from federal lands
    - 14% of US oil production and 2% of US gas production is from offshore
    - 56% of the emissions effects of increased leasing on federal land would be due to oil, and the remaining 44% due to gas
- We assume that the emissions effects of increased offshore drilling leasing would be proportional to the effects of increased federal leasing

- Therefore to adjust RFF's onshore estimate to include offshore effects, we use the multiplier 0.56 * (12 + 14)/12 + 0.44 * (11 + 2)/11 = **1.733**

RFF do not give year-by-year emissions effects, but they provide a chart showing how the emissions effects change over time.



We interpret the effects as follows:

- No emissions effects for the first five years
- From five years after the start until the end of the time period (2050), the annual emissions effects decline linearly until they are 20% of their peak levels

This allows us to estimate the year-by-year emissions effects, ensuring that they sum to 0.6 and 2.1 Gt in the low and high estimates respectively.

When accounting for [policy persistence]() we assume that expanded leasing has a 50% chance of surviving each next four-year term. This leads to very steep discounts by the end of the 2025-2050 period.

We also re-ran the calculations under the alternative assumption that expanded oil and gas leasing, if it survives past 2033, will endure through 2050. Under this assumption, expected emissions effects were 8% higher.

IRA Repeal

Full repeal

When processing both the Rhodium and Energy Innovation estimates, we converted the 2030 and 2035 emissions effects into year-by-year emissions effects, assuming that emissions effects changed linearly between 2025 and 2030 and between 2030 and 2035. This meant we were able to account for policy persistence, assuming that a full IRA repeal has a 50% probability of reversal every four-year term.

The mid estimate averages the Rhodium and Energy Innovation estimates, effectively applying a 3% discount to the persistence-adjusted Rhodium estimate. This same discount is applied to Rhodium's high/low estimates to generate our best guess low and high estimates.

Tech neutral tax credits

For the BNEF and REPEAT capacity growth estimates respectively, we assume constant cumulative capacity additions throughout 2025-35. We account for policy persistence with a 50% probability of reversal every four-year term. Then we convert capacity to generation and generation to averted emissions.

The mid estimate is the geometric mean of the BNEF and REPEAT estimates. The low and high estimates are generated from weighted geometric means of the BNEF and REPEAT estimates:

- For the lower estimate we take a geometric mean with weight 4 on the BNEF estimate and weight -1 on the REPEAT estimate
- For the higher estimate we take a geometric mean with the weights reversed.

Wind & Solar

We convert REPEAT 2035 generation estimates into estimated cumulative 2025-35 generation effects for all power sources. This allows us to model how clean generation rises and gas/coal generation falls due to the IRA.

We use EIA emissions intensity estimates to model the emissions effects of declining coal and gas generation in the IRA ("current policy") scenario.

We then allocate these emissions effects between wind and solar in proportion to the clean energy generated by each source during the period 2025-35.

When processing BNEF data, we start by converting it into an estimate of wind/solar/storage emissions effects in 2025-35 as described above. Since the estimate bundles effects of wind, solar and storage, we estimate the share of benefits attributable to wind / solar by (1) assuming that 20% of emissions benefits come from storage and (2) allocating the remaining 80% between wind and solar in the proportion of wind and solar benefits according to our REPEAT-based estimates.

For the mid estimate, take the geometric mean of BNEF and REPEAT estimates, with double weight on the BNEF estimate. BNEF produces its estimates for market insiders who want accurate predictions of future dynamics, which we think makes them reliable.

We set the REPEAT mid estimate as the best guess high estimate, and set the low estimate so that the ratio between mid and low is the same as between high and mid.

Then adjust for policy persistence by applying the usual method to the REPEAT data after we convert their 2035 estimates into year-by-year estimates. We use the ratio between the persistence-adjusted values and the raw values as a multiplier to convert our best guess estimates into persistence-adjusted best estimates.

EVs

For EVs we only had one source, REPEAT, which was more optimistic about the importance of the IRA than BNEF.

REPEAT estimates the energy consumption of different fuels for different vehicle classes in the US from 2025 to 2050 under different policy scenarios . We used estimates of fuel emissions density to convert this into differences in emissions outcomes between the case in which the IRA is preserved (Current Policies), and a scenario in which pre-IRA policies are maintained (IIJA only). REPEAT gives conservative, central and optimistic estimates, which we process in the same way.

Finally, we made an adjustment to account for the fact that our other IRA estimates are lower than the corresponding REPEAT estimates. Our final mid estimate for emissions effects of IRA *solar* repeal was only 36% of the REPEAT estimate. We use the square root of this, 0.59, as a multiplier discount to the REPEAT estimate. This reflects our suspicion that the REPEAT EV estimates are likely to be an overestimate, although EV adoption may be less sensitive to the IRA than the scaling of wind and solar (making it less likely that REPEAT is way off the mark).

Permitting Reform

Speed up permitting

The IMF provide estimates on how accelerating permit delays from 4.5 years to 1.5 years would affect clean energy capacity and investment, and GHG emissions, between 2021 and 2030. We convert this into an estimate of how IRA repeal in 2025 would affect 2025-35 emissions as follows:

- We derived the ratio between investment and additional clean energy capacity by comparing IMF estimates of additional investment and averted emissions up to 2030.

    - We assumed that additional clean capacity was proportional to additional investment
    - We assumed that capacity came online as soon as the investment was made
    - Working backwards from the emissions benefits, we are able to infer the additional capacity (in Mt CO_2e averted per year) per unit of investment
- We estimated that the effect of accelerated permitting on investment would decline to zero between 2030 and 2035. This allowed us to estimate the year-by-year effects on investment in the period 2025-35
- We combined the two above estimates to estimate total additional clean capacity, and therefore emissions, over 2025-35.

Low and high estimates were arbitrarily set 1.75 times lower/higher than the mid estimate.

Address clean energy headwinds

Rhodium estimate the effect that clean energy "Headwinds" will have on clean energy capacity. We assumed that capacity additions were constant over 2025-35, and therefore occurred an average of 5.5 years before the end of the period 2025-35. This allows us to convert capacity to generation. We converted this into emissions averted.

Double interconnection rate

According to the Queued Up report, only 20% of projects that enter the interconnection queue subsequently gain approval. We assume that radically improved policy leads to the approval of an additional 13-30 percentage points of wind and solar capacity in the interconnection queue, and that new additions to the queue will continue broadly as they have since the passage of the IRA (350-800 GW of additional wind and solar capacity in the queue each year). New clean capacity is assumed to come online at a delay of five years, and to displace emissions at the same rate that we assume elsewhere in our analysis. These calculations were performed as a Monte Carlo simulation.

Accelerate transmission growth

RMI estimate the effects of the EPRA on emissions through accelerated transmission growth. They assume that additional clean generation displaces gas generation. We use more conservative assumptions about the emissions averted by additional clean energy generation, in line with those we use elsewhere in our analysis.

When accounting for policy persistence we assigned a 90% probability that the policy survives each four year term, since transmission reform would likely be part of a bipartisan bill requiring a 60% congressional majority. This means that by 2050, there is only a 53% chance that accelerated transmission growth remains in place. Under the alternative assumption that if the policy survives to 2033, it endures through 2050, the expected emissions impacts are 3% higher.

We infer year-by-year emissions effects, account for policy persistence, and sum to estimate cumulative 2025-35 effects.

The mid estimate is set to the geometric mean of the RMI and REPEAT estimates. To calculate the high and low estimates we use the following approach:

- Calculate the standard deviation of
  - The logarithm of the RMI estimate
  - The logarithm of the REPEAT estimate
- Set the low / high estimate as the exponent of { the logarithm of the mid estimate + / - the standard deviation calculated above }

This draws upon variation between RMI and REPEAT estimates while giving the estimates positive skew, which is what we expect from emissions effects, which are probably the product of multiple unknown variables.

Comprehensive permitting reform

The permitting package is assumed to have 20-100% of the benefits of permitting and interconnection estimated above, and 50% of the transmission benefits.

We use a Monte Carlo simulation in which the effects of permitting, interconnection and transmission are modeled lognormally (using high-low estimates as 5th and 95th percentiles). The 20-100% proportions are also modeled lognormally.

We account for the fact that IRA repeal would likely decrease the benefits of permitting reform. We assume that:

- Full IRA repeal would decrease the benefits by 17-69% (5th and 95th percentiles of a lognormal distribution), in line with BNEF and REPEAT estimates that IRA repeal (BNEF) or reversion to pre-Biden climate policy (REPEAT) would decrease clean energy capacity buildout by 17% (BNEF) or 69% (REPEAT). These estimates form the 5th and 95th percentiles of a lognormal distribution.
- The extent of IRA repeal is modeled uniformly between 0 and 1. This is used as a multiplier on the IRA repeal discount modeled above.

Combined, this represents a discount with 90% confidence interval (-46% to -2%).

LPO

The LPO takes a hits-based approach with its loans: much of its portfolio will have modest counterfactual effects, some of its loans will be lost, and a few will provide a valuable boost to companies with significant effects on global climate progress.

Tesla is probably the LPO's biggest success. We construct an estimate of the value of the LPO Tesla loan to estimate the value of the LPO as a whole. We assume that:

- The Tesla loan represents 10-100% (90% confidence interval of a lognormal distribution) of the emissions value of LPO's loans to date
- The LPO has made around $137.4B in loans so far
- Future LPO loans will be as cost-effective as those in the past

Tesla case study

LPO's Tesla loan likely added value in two ways:

- It may have saved Tesla from eventual bankruptcy, thereby accelerating the global adoption of EVs
- It likely accelerated the growth of Tesla[7], thereby accelerating the global adoption of EVs

Our approach to modeling the value of the Tesla loan is to

1. Model the emissions value of accelerating the global adoption of EVs
2. Model the degree to which the LPO loan accelerated the global adoption of EVs

For **(1)**, we combine projections about future travel and emissions trends to forecast the emissions averted by EVs each year from 2015 to 2050:

- Global vehicle km travelled (Knobloch et al., 2020) in 2015, 2030, 2050. This was modeled as changing linearly between time points.
- Emissions intensities of petrol cars per km (Knobloch et al., 2020) in 2015, 2030, 2040 and 2050
- Emissions intensity of EVs per km. For this we used the Knobloch et al. (2020) 2015 estimate, and modeled it as decreasing over time in line with global electricity emissions intensity. We used three different estimates to form slow, mid and optimistic emissions trajectories:
    - Slow: emissions intensity of electricity decreasing 0.7%/yr from 2015-30 and 0.34%/yr from 2030-50, in line with Knobloch et al., (2020)
    - Mid: decreasing 1.64%/yr, in line with "New Policies Scenario" from IEA, 2016
    - Optimistic: decreasing 8.18%/yr, in line with "well below 2C" pathway from IEA, 2016
- EV adoption rate: Assume they stand at 3% in 2024. Use BNEF forecast that it rises to 15% in 2030, 35% in 2040 and 55% in 2050. Assume the adoption rate increases exponentially between 2024 and 2030, and piecewise linearly thereafter

By calculating the difference in emissions per km between petrol and electric vehicles each year, we can model the emissions averted by EVs each year up to 2050. We can model the acceleration of EV adoption by moving the EV adoption rates forward by one year (2030's adoption rate becomes 2029's adoption rate, 2031's becomes 2030's, and so on) and

[7] The $465 million Department of Energy loan through the Advanced Technology Vehicle Manufacturing program allowed Tesla to retool the former NUMMI factory in Fremont, California, and to design and manufacture their first mass-market vehicle, the Model S luxury sedan, which launched in 2012.

observing the increase in emissions averted. We find that accelerating EV adoption globally by one year averts approximately 1.08 Gt CO_2e.

For **(2)** We conduct a Monte Carlo simulation:

a. We account for varying rates of EV adoption with a lognormal multiplier (90% C.I. (0.56, 1.64))
    - EIA estimated in 2021 that 31% of global light vehicle stocks would be EVs in 2050. This is only 56% of our BNEF estimate of 55% by 2050
    - Morgan Stanley estimates 90% of car sales globally will be EVs. Interpreted generously, this suggests a 90% adoption rate, which is 64% more than out BNEF estimate

b. From the different decarbonization estimates in **(1)**, we model the effect of accelerating global EV adoption by one year (lognormal, 90% C.I. (0.67, 2.2) GT CO_2e)

c. Tesla accelerated global EV adoption by 1.5 to 6 years (5th and 95th percentiles of a lognormal distribution)

d. The loan saved Tesla from failure with probability 1% to 50% (5th and 95th percentiles of a lognormal distribution truncated at 1)

e. The loan accelerated Tesla's growth by 0.2 to 2 years (5th and 95th percentiles of a lognormal distribution)

f. Accelerating Tesla by one year accelerates global EV adoption by 0.35 to 0.93 years (Beta distribution with parameters 4 and 2)

Therefore the benefits of the LPO loan are the sum of:

- The benefits of saving Tesla (a * b * c * d above)
- The benefits of accelerating Tesla's growth. This only counts if the loan did not save Tesla from failing (a * b * (1 - d) * e * f above)

Since we assume that the Tesla loan is 10-100% of the benefits of the LPO so far, the full effects of the LPO are 1-10x the effects of the Tesla loan.

LPO reference Scenario

The reference scenario is that the LPO uses all of its current loan authority of around $300B, and makes all of its loans to clean energy projects. Since the LPO has made around $137.4B in loans so far, the value of the reference scenario is the past value of the LPO, multiplied by 300 / 137.4 = 2.183.

LPO Policy scenarios

LPO dormant & announced loans scrapped
This is equivalent to losing 100% of the value of the LPO.

LPO dormant

An estimated $54.5B in announced loans would go ahead, leaving approximately $244.4B unused. We assume that this represents a loss of 244.5/300 = 81.5% of the value of the LPO.

50% increase in LPO efficiency
The LPO averts 50% more emissions than in the reference scenario.

30% of LPO loans diverted to fossil projects
We assume that loans for fossil innovation projects would cause additional emissions, with 10-100% (90% confidence interval of a lognormal distribution) of the magnitude of the emissions averted by clean energy loans. The full effects are thus:

- 30% drop in loans to clean energy projects, causing 30% drop in emissions averted by the LPO
- 30% of funds going to fossil fuels, at 10-100% the emissions effects of clean energy loans. This causes a further 3-30 percentage point drop in the net emissions averted by the LPO
- Combined, this is a 33-60 percentage point drop in the emissions averted by the LPO compared to the reference scenario.

30% of LPO loans diverted to fossil projects and LPO efficiency increased by 50%
The new emissions benefits of the LPO are 1.5 * (1 - 0.3 - (0.03 to 0.3)), which is equal to 1.5 * (0.4 to 0.67) = 0.6 to 1. This equates to approximately a 0 to 40 percentage point reduction in emissions averted by the LPO compared to the reference scenario.

DOE

The DOE takes a multi-faceted approach to innovation funding. To estimate its value, we analyze fracking, a major historical success and a potential future success, Enhanced Geothermal Systems (EGS). We then combine these analyses to project the DOE's future impact.

We repeat each case study twice, under each of two worldviews: Carter Contingency view[8] and Incrementalist Innovation view[9].

Our best guess estimate for the historical benefits of DOE program spending (which amounted to $158B in 2016 dollars in the period 1978-2018) is the unweighted geometric mean of:

1. Estimate based on fracking under Carter Contingency view
2. Estimate based on fracking under Incrementalist Innovation view

[8] On this view, early government investment can radically accelerate technological progress, to the extent that if President Carter had been given another term, we might have had affordable solar energy in the 1980s. Under this view, the government can significantly shape trajectories and can accelerate significantly.
[9] On this view, anything that the government or other actors do cannot be far ahead of the curve. Innovation unfolds more gradually and is less sensitive to who does what when.

3. Estimate based on EGS under Carter Contingency view
4. Estimate based on EGS under Incrementalist Innovation view

We form low/mid/high estimates, each of which is the geometric mean of the low/mid/high estimates of the models above.

In the fracking estimates, we assume that fracking represents 10-100% of the historical benefits of the DOE. In the EGS estimates, we assume that DOE spending is 10-100% as cost-effective as EGS spending would be.

Fracking case study

Benefits of shale revolution
We collected three primary estimates of fracking's emissions effects:
- Council of Economic Advisers (CEA): 6.8 GT CO_2e (2005-2017)
- Energy Information Administration (EIA): 2.4 GT CO_2e (2006-2017)
- Breakthrough Institute: Validated EIA's estimate (their 2008-2012 estimate was only 7% higher)

We adjusted these estimates by:
- Applying a 15% discount to account for increased US coal exports (based on Breakthrough Institute analysis)
- Assuming the all-time effects are 1.4-4.0x greater than the 2005-17 effects to account for continued but diminishing benefits

This yielded a total impact estimate of 4.22 GT CO_2e (90% CI: 1.32-14.3 GT).

We assume that accelerating the shale revolution by one year has one-twelfth of the benefits of the shale revolution as a whole. We expect that the benefits of fracking decrease over time, as alternatives to coal become more abundant.

DOE contribution to fracking
We modeled DOE's impact through two mechanisms:
- Making the shale revolution more likely
- Accelerating its development

We analyzed this under the Carter Contingency view and Incrementalist Innovation view described above:
- Carter Contingency view:
  - DOE increased probability of the shale revolution by 25-90 percentage points
  - Accelerated development by 5-12 years (this is only counted in scenarios when the shale revolution would have happened anyway)
  - Results in 3.15 GT CO_2e impact (90% CI: 0.99-10.50 GT)
- Incrementalist Innovation view:

    - DOE increased probability of the shale revolution by 2-35 percentage points
    - Accelerated development by 3-12 years (this is only counted in scenarios when the shale revolution would have happened anyway)
    - Results in 1.62 GT CO_2e impact (90% CI: 0.56-5.11 GT)

Value of the DOE
To convert these into estimates of the value of the DOE, we assumed that fracking benefits are 10-100% of those of the DOE. In other words, the full value of the DOE is 1-10x higher than its fracking benefits.

Geothermal case study

Value of EGS adoption
We modeled the value of global EGS capacity increasing to 100GW by 2050 by:

- Projecting EGS capacity, generation, and emissions averted per unit clean energy (2025-2050)
    - **Capacity** was assumed to start at 0.025GW in 2025, increase exponentially to 10GW in 2030, then linearly increase to 100GW in 2050
    - **Generation** per GW-year was 6.57 TWh, corresponding to a 75% capacity factor (IEA)
    - For **emissions averted per unit clean energy** we started with the 0.19 Mt per TWh that we use for renewables, applied a 50% increase to account for the increased value of firm power, and a further 30% increase to account for the fact that *global* emissions intensity of electricity is higher than for the US. This brought us to 0.37 Mt per TWh. We assume that this will decrease in line with decreasing emissions intensity of electricity.
- Analyzing under different electricity decarbonization scenarios:
    - Slow: emissions intensity of electricity decreasing 0.7%/yr from 2015-30 and 0.34%/yr from 2030-50, in line with Knobloch et al., (2020)
    - Mid: decreasing 1.64%/yr, in line with “New Policies Scenario” from IEA, 2016
    - Optimistic: decreasing 8.18%/yr, in line with “well below 2C” pathway from IEA, 2016

This approach suggests that the value of 100 GW of EGS potential by 2050 will avert 5.21 Gt CO_2e (range: 1.31 to 6.27).

DOE contribution to EGS
We model global EGS capacity in 2050 as a lognormal distribution. In our model a $25B DOE funding package acts as a multiplier on this distribution. Once we estimate the additional capacity attributable to the DOE, we can convert this to emissions using the estimate above for the value of 100GW globally by 2050.

Our approach is as follows

- The baseline distribution of global EGS capacity in 2050 is a lognormal distribution with 90th percentile 300 GW and 98th percentile 1000 GW. Let us call this random variable **Y**. By construction, this gives a 10% probability of EGS reaching 300GW by 2050, which we call "scaling".
- If the probability of EGS scaling *without* DOE funding is p%, we use the inverse normal distribution to calculate the constant $\mathbf{k_1}$ by which **Y** must be multiplied to achieve this probability of scaling. Thus $P(\mathbf{k_1 Y} > 300) = p\%$
- If the probability of EGS scaling *with* DOE funding is q%, we use the same method to calculate the constant $\mathbf{k_2}$ by which **Y** must be multiplied to achieve this probability of scaling. Thus $P(\mathbf{k_2 Y} > 300) = q\%$
- Therefore the effect of DOE funding is to increase global 2050 EGS capacity by $(\mathbf{k_2} - \mathbf{k_1})\mathbf{Y}$ GW
- Combine this with our estimate for the value of reaching 100 GW of global capacity in 2050 to get the emissions benefits of DOE funding.

We model:
- The emissions effect (in Gt CO_2e) of 100 GW global EGS capacity by 2050 as normal, with mean 5 and SD 1.24 (approximating our above estimate of 5.21 Gt CO_2e (range: 1.31 to 6.27)).
- The odds of EGS scaling to 300 GW globally by 2050 as lognormally distributed with 90% C.I. (0.005, 0.5), corresponding to a probability of 0.5% to 33%.

We modeled this under two frameworks:
- Carter Contingency view:
  - DOE increases odds of EGS scaling by 1.2-20x
  - Results in 0.83 GT CO2e impact (90% CI: 0.0068-40 GT)
- Incrementalist Innovation view:
  - DOE funding increases odds of EGS scaling by 1.2-3.3x
  - Results in 0.226 GT CO2e impact (90% CI: 0.0056-8.12 GT)

Value of the DOE

Under each of the views above, we assume that the cost-effectiveness of DOE spending is 10-100% that of the $25B EGS innovation funding we modeled.

DOE reference scenario

Our reference scenario is $330B of DOE innovation spending on clean energy projects in the period 2025-2035.

DOE spending in the period 1978-2018 totaled $208B in 2025 dollars, so the reference scenario is 330 / 208 = 1.587 more valuable than the past value of the DOE.

DOE spending is assumed to be 10-100% as cost-effective as the $25B EGS funding we modeled, so the reference scenario is (0.1 to 1) * (330 / 25) = 1.3 to 13 times more impactful than the EGS innovation funding package.

As described above, our final estimate for the value of the DOE is a geometric mean of sub-estimates.

DOE policy scenarios

10% / 35% DOE efficiency increase
A 10% / 35% increase in the emissions averted by the DOE. We assume that this is not reversed by future administrations.

20% / 40% DOE budget cut
A 20% / 40% increase in the emissions averted by the DOE while the cuts persist. We assume a 50% chance that the cut is reversed in 2029 and that if it is not reversed, it endures through 2035.

OCED cut
We assume that OCED funding is 1-5 times more effective than non-OCED DOE funding. OCED currently represents around 10% of DOE program budgets. OCED's share of the DOE's total impact is thus 0.1 * (1 to 5) / (0.9 + 0.1 * (1 to 5)) = 0.1 to 0.357. Cutting OCED reduces DOE's emissions reduction by 10-36% compared to the reference scenario.

Probability of policy change

We report our estimates on the probability of policy change below.
These are subjective expert estimates based on (a) a read of the literature and (b) conversations with experts close to the policy process, with details in the "Commentary" column.

Policy lever	P (min)	P (max)	Commentary
Advocacy to prevent full IRA repeal	0.2	0.4	Full repeal is clearly considered unlikely; recent Heatmap expert survey estimate for full repeal is in the middle here, adding some uncertainty around it
Advocacy to prevent repeal of IRA tech neutral tax credits	0.2	0.7	
Wind - Advocacy to prevent IRA repeal	0.4	0.8	Trump clearly hates wind and this is generally considered

			most at risk
Solar - Advocacy to prevent IRA repeal	0.2	0.7	Clearly more popular than wind, less at risk
EVs - Advocacy to prevent IRA repeal	0.6	0.9	
Fight EPA rollbacks	0.8	0.95	essentially baked in
Advocacy for comprehensive permitting reform	0.4	0.8	
Advocacy for accelerating clean energy permitting	0.4	0.8	Around the midline of recent Heatmap estimate, uncertainty added around that
Advocacy to double interconnection rate	0.4	0.8	would be part of major permitting reform
Advocacy to prevent expanded oil and gas leasing	0.8	0.95	essentially baked in
Oppose LNG export permits	0.8	0.95	essentially baked in
Push for accelerated transmission growth	0.4	0.8	would be part of major permitting reform
Advocacy to avoid 20% DOE budget cut	0.6	0.8	Generally what experts we talked to expected to happen
Advocacy to avoid 40% DOE budget cut	0.2	0.4	Unlikely, more radical than what seems feasible in close policy conditions
Push for 10% increase in DOE efficiency	0.6	0.9	default
Push for 35% increase in DOE efficiency	0.2	0.5	seems large
Advocacy to avoid OCED cut	0.4	0.7	quite possible, libertarian wing winning out / small government attitudes
Preventing LPO scrapping announced loans & going dormant	0.1	0.3	unlikely to happen, too extreme
Preventing LPO going dormant	0.2	0.5	unlikely to happen, too extreme
Push for 50% increase in LPO efficiency	0.2	0.5	possible but ambitious
Prevent diversion of 30% of LPO loans to fossil fuels	0.5	0.9	More likely than not for LPO to expand to fossil fuels

Philanthropic affectability

We report our estimates on the relative philanthropic affectability below.

These are subjective expert estimates based on (a) a read of the literature and (b) conversations with experts close to the policy process, with details in the "Commentary" column.

Generally, we seek to apply various heuristics across these interventions – increasing philanthropic affectability when interventions are depoliticized, decreasing it when they are very politicized and increasing estimates when interventions leverage existing philanthropic strategies with proven track record (such as law suits or "legislative subsidy", providing expertise for lawmakers in depoliticized technical policy domains).

Policy lever	**Affectability (min)**	**Affectability (max)**	**Commentary**
Advocacy to prevent full IRA repeal	0.06	0.42	
Advocacy to prevent repeal of IRA tech neutral tax credits	0.04	0.71	
Wind - Advocacy to prevent IRA repeal	0.00	0.22	
Solar - Advocacy to prevent IRA repeal	0.06	0.42	
EVs - Advocacy to prevent IRA repeal	0.06	0.42	
Fight EPA rollbacks	0.11	0.75	proven tractable intervention
Advocacy for comprehensive permitting reform	0.29	0.79	
Advocacy for accelerating clean energy permitting	0.29	0.79	medium politicized, legislative subsidy and coalitional support
Advocacy to double interconnection rate	0.11	0.75	proven tractable intervention
Advocacy to prevent expanded oil and gas leasing	0.03	0.32	proven tractable intervention
Oppose LNG export permits	0.00	0.66	proven tractable intervention

Push for accelerated transmission growth	0.29	0.79	medium politicized, legislative subsidy and coalitional support
Advocacy to avoid 20% DOE budget cut	0.21	0.71	relatively depoliticized, everyone wants innovation
Advocacy to avoid 40% DOE budget cut	0.21	0.71	relatively depoliticized, everyone wants innovation, but also fiscal
Push for 10% increase in DOE efficiency	0.50	0.98	relatively depoliticized, everyone wants efficiency, advocacy and ideas can matter here (legislative subsidy)
Push for 35% increase in DOE efficiency	0.50	0.98	relatively depoliticized, everyone wants efficiency, advocacy and ideas can matter here (legislative subsidy)
Advocacy to avoid OCED cut	0.03	0.89	more politicized
Preventing LPO scrapping announced loans & going dormant	0.29	0.79	medium politicized, legislative subsidy and coalitional support

Preventing LPO going dormant	0.29	0.79	medium politicized, legislative subsidy and coalitional support
Push for 50% increase in LPO efficiency	0.50	0.98	relatively depoliticized, everyone wants efficiency, advocacy and ideas can matter here (legislative subsidy)
Prevent diversion of 30% of LPO loans to fossil fuels	0.00	0.22	highly politicized

Additionality

We now discuss how we operationalized additionality.

Quantitative analysis

Our quantitative analysis proceeds in three steps:

- (1) Estimating the funding available for different broad sectors, adjusting data from ClimateWorks to make it an estimate of actual funding available
- (2)Estimating how those funding buckets translate into funding for the discussed strategies.
- (3) Translating these estimates into additionality estimates.

Step 1: Adjusting ClimateWorks Data: From ClimateWorks data to current averages of funding for different philanthropic sectors

We base our data analysis on ClimateWorks[10] data on philanthropic funding and perform various adjustments to make the data closer to a current estimate of available funds, from foundations and individuals, for different intervention areas.

Adjusting for underreporting

We know from conversations with ClimateWorks that their most current data is an underreporting given data lags. We take it into account by adjusting ("boosting") the given philanthropic foundation data to reflect the funding landscape more accurately. We do that by applying multipliers to each data set in each ClimateWorks funding data report. The multipliers are calculated by comparing their latest available total foundation giving data with the figures in past reports. For each report, we calculate the total foundation giving over the given time period, such as 2015–2019 or 2016–2020. We then divide the total foundation giving from the latest report by the total from the past report for the same period. This gives us scaling factors for each period that correct for underreporting. For the latest report, we use the average of the before-derived multipliers.

Accounting for individual funding

Given that ClimateWorks only captures foundations but individuals dominate climate philanthropy, we tried to roughly estimate the real funding pools charities have access to by multiplying the foundation data (that includes our best guess for underreporting) by a factor of 3. This factor is derived by analyzing the ratio of individual giving to foundation

[10] Roeyer, Hannah, et al. "Funding Trends: Climate Change Mitigation Philanthropy." ClimateWorks Foundation, Sept. 2020, www.climateworks.org/report/funding-trends-climate-change-mitigation-philanthropy/.; Desanlis, Helene, et al. "Funding Trends 2021: Climate Change Mitigation Philanthropy." ClimateWorks Foundation, Oct. 2021, www.climateworks.org/report/funding-trends-2021-climate-change-mitigation-philanthropy/.; Desanlis, Helene, et al. "Funding Trends 2022: Climate Change Mitigation Philanthropy." ClimateWorks Foundation, Oct. 2022, www.climateworks.org/report/funding-trends-2022/.; Desanlis, Helene, et al. "Funding Trends 2023: Climate Change Mitigation Philanthropy." ClimateWorks Foundation, Nov. 2023, www.climateworks.org/report/funding-trends-2023/.; Esmaeili, Narine et al. "Funding Trends 2024: Climate Change Mitigation Philanthropy." ClimateWorks Foundation, Dec. 2024, www.climateworks.org/report/funding-trends-2024/.

funding from ClimateWorks data over time, estimating the minimum and maximum ratios for missing years and then averaging these ratios.

Step 2: From broad sectors to intervention levers

We link the broad ClimateWorks funding sectors (e.g. “Challenge Fossil”) to our specific policy intervention levers (e.g. “Regulatory rollbacks at the EPA”) and assign a low, medium and high share of total sector funding to each policy lever.

These estimates are highly uncertain, but based on considerations such as (a) what share usually goes for a specific intervention (e.g. when “opposing natural gas” is mentioned as one of ten priorities under “challenge fossil” description this would make it unlikely that opposing LNG exports would be the single focus of the “challenge fossil” bucket), (b) the qualitative complement and other impressions on how climate philanthropists are prioritizing between different interventions (for example, the salience of defense via grassroots mobilization in appeals by Big Green makes plausible that a high share of “Public Engagement” funding goes to oppositional tactics / engagement and mobilization around opposing policies of the Administration).

Using these proportions, we calculate a best estimate along with a range of funding associated with each policy intervention lever by multiplying the total estimated funding for each sector by its assigned proportion for that policy lever and summing these values across all sectors.

As an example, we show the calculation for *EPA Rollbacks* below:

Estimated foundation funding for preventing EPA Rollbacks

		Estimate					
		Low		Mid		High	
Sector	**Foundation funding (USD million)**	**Share**	**USD million**	**Share**	**USD million**	**Share**	**USD million**
Challenge fossil	267.75	0.1	26.775	0.2	53.55	0.4	107.1
Public Engagement	645.75	0.01	6.46	0.15	96.86	0.35	226.01
	Total		**33.23**		**150.41**		**333.11**

In this way we estimate that the funding available for preventing EPA rollbacks is $150M (range: $33M to $333M). What matters here is the comparison between different policy levers, not the absolute amounts, so it does not matter if our funding estimates are consistently too high or consistently too low, as long as they are unbiased.

Step 3: Towards additionality estimates

To translate these funding estimates to estimates of the additionality of extra funding, we construct a transformation from funding to funding additionality in which the highest funding additionality is 90% and the lowest is 10%.

Funding additionality, expressed as odds, is modeled as a decreasing exponential. This has desirable properties:

- Additionality decreases as available funding increases
- In this model, funding additionality is always between 0 and 1
- When funding is zero, additionality is 1

The model is:

$$\text{funding additionality expressed as odds} = \text{constant} \cdot \text{funding}^{index}$$

The constant and index are chosen so that the lowest funding estimate leads to an additionality of 90% and the highest funding estimate leads to an additionality of 10%.

Constant = 179
Index = -1.246

This leads to the following relationship between funding and additionality:

The transformation from funding to funding additionality, with lowest and highest funding estimates displayed.

This allows us to form low and high estimates for the additionality of philanthropic funding for each policy lever.

The key weakness of this approach is that it does not account for the *size* of each field. In reality, $50M would represent abundance for small sectors, and a very lean year for large sectors. We think that despite the noise this introduces to our calculations, it is still worthwhile to incorporate funding data into our additionality estimates.

Qualitative complement

Given that **(a)** the ClimateWorks categories are very broad and make it difficult to make more precise inferences, **(b)** climate philanthropy is dominated by individual giving and **(c)** large "Big Green" organizations have a disproportionate impact on the perception of energy and climate policy and priorities, we also complement our quantitative analysis with a qualitative comparative analysis analyzing the key themes emphasized in a number of articles analyzing the priorities of the climate movement.

The result of this analysis is summarized in Appendix A: Philanthropic Responses.

Other contents

Here we discuss data analysis not part of the philanthropic prioritization model.

Imbalance of climate philanthropy

To analyze the distribution of climate philanthropy between Eco-Right and Left-leaning organizations and the "Big Green," we selected key organizations in each category.

Eco-Right: ClearPath Foundation, Conservative Energy Network (CEN), Niskanen Center, Climate Leadership Council (CLC), Citizens for Responsible Energy Solutions Forum (CRES Forum), Alliance for Market Solutions (AMS), Deploy/US, American Conservation Coalition (ACC), RepublicEn, Evangelical Environmental Network (EEN), R Street Institute

Left-leaning: NRDC, Greenpeace, Sunrise Movement, Sierra Club

Big Green (inclusive category): NRDC, Greenpeace, Sunrise Movement, Sierra Club, Nature Conservancy, Environmental Defense Fund

The distinction between “left-leaning” and “Big Green” reflects the fact that the Environmental Defense Fund and the Nature Conservancy have a somewhat less partisan branding than other Big Green groups.

We extracted their total revenue numbers over time from their 990 tax forms available through ProPublica. For one organization, we obtained revenue figures directly from a personal contact.

Since organizations report on different fiscal years, we adjusted all records to align with a standard calendar year ending in December. Additionally, for multi-purpose organizations (in particular think tanks with a broad remit beyond energy and climate), we adjusted for the climate/energy share of funding based on staff share working on climate and energy issues.

The extracted and adjusted revenue data can be found here:
Funding_trajectories_EcoRight_LeftLeaning_BigGreen [PUBLIC]