A Narrative on Learning and Monte Carlo Simulation to Confirm the Likelihood of a Cost-Effective Transition to Decarbonized Ethanol Resources

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October 2024

This research paper was commissioned by the EFI Foundation and represents the views and conclusions of the author(s).

The purpose of this commissioned analysis was to test the reasonableness of the cost estimates for the various ethanol decarbonization measures in the report, which were drawn largely from desktop research. The cost estimates were benchmarked using established statistical methodologies for Bayesian Inference, including learning rates and Monte Carlo simulations. The statistical analysis generally supported the reasonableness of the reported cost estimates.

The EFI Foundation has not endorsed or approved the statements and conclusions contained in these documents but will be sharing this work as part of the project process.

About the Author

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Author of more than 320 reports, journal articles, and book chapters, Skip’s expertise includes benefit-cost assessments, the review of energy and non-energy benefits, exploring resource costs and constraints, and assessing the net employment and macroeconomic impacts of what he calls “Innovation Scenarios” as well as the more typical energy and climate policy scenarios.

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Skip has a 1988 master’s degree in resource economics from Antioch University. And he has also undertaken work and given many lectures in a variety of countries including Australia, Brussels, China, France, Japan, Luxembourg, Netherlands, Portugal, South Africa, Spain, and the United States, among others.

Abstract

This document explores the application of Bayesian inference and Monte Carlo simulations to evaluate the cost-effectiveness and likelihood of decarbonizing ethanol. It highlights the effects of learning and the economic benefits of reducing greenhouse gas emissions through ethanol use. The analysis uses experience curves to estimate the scale of possible cost reductions in ethanol production over time, while Monte Carlo simulations provide a range of potential outcomes for future costs. The findings suggest decarbonizing ethanol can lead to lower costs and significant environmental and economic benefits.

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I. Introduction

The purpose of this analysis was to apply techniques of Bayesian inference in order to provide an independent assessment of the reasonableness of the cost of GHG emissions reductions presented in the EFI Foundation report "A Strategic Roadmap for Decarbonizing the U.S. Ethanol Industry." Specifically, the analysis was designed to confirm or examine the likelihood of a similar or comparable set of outcomes as characterized in that report. In this case, we explore the likelihood of similar or improved, or an even better, set of outcomes than posed by the main narrative and analysis. Bayesian inference is seen as an important technique in statistics that relies on a different set of metrics to test and provide an important confirmation in the analysis of the ethanol story.[1]

II. Comparing the Costs of Ethanol Decarbonization Strategies to the Benefits

Before we confirm the likelihood of the cost estimates of various measures to decarbonize ethanol resources, we first examine the costs in relation to the economic and social benefits of transitioning to decarbonized ethanol resources.

While the scope of the EFI Foundation study did not include a benefit/cost analysis, a complete analysis would document an array of both costs and benefits. Here, the suggestion is that the benefits or transition to decarbonized ethanol might be summarized as the avoided Social Cost of Carbon (SCC) or the Social Cost of Carbon Dioxide (SC-CO_2).

[1] As summarized in, https://en.wikipedia.org/wiki/Bayesian_inference, this usually is a method of statistical inference used to update a working assessment or a prior analysis as more evidence, or as more supplemental information becomes available. For a more complete background of this idea, see also, McGrayne, Sharon Bertsch. The Theory That Would Not Die: How Bayes' Rule Cracked the Enigma Code, Hunted Down Russian Submarines and Emerged Triumphant From Two Centuries of Controversy. New Haven, CT: Yale University Press, 2012. https://yalebooks.yale.edu/9780300188226/the-theory-that-would-not-die.

This is an estimate, in dollars, of the many economic damages that would result from emitting one additional ton of carbon dioxide into the atmosphere. In effect, the SC-CO_2 translates the effects of climate change into economic terms. This reflects climate impacts such as temperature increase and sea level rise, as those changes impact agriculture, health, energy use, and other aspects of the economy. Rennert et al. (2022) show that improved socioeconomic projections, together with both updated climate models and climate damage functions, reveal a preferred mean SC-CO_2 estimate that is on the order of $185 per ton of CO_2 ($44–$413 per ton of CO_2: 5%–95% range, 2020 US dollars).[i] In other words, at an economic cost of $185 per ton, the investment in decarbonization techniques, which end up costing less than $185, can actually benefit both the market and the economy. This is significantly higher than an earlier US government value of $51 per t$CO_2$. At $185 per ton of CO_2 avoided, the benefit is significantly higher than the range of aggregate costs associated with the many different techniques or technology pathways that might reduce carbon dioxide emissions from the use of ethanol fuels.

Ricke et al. (2018), at the Scripps Institution of Oceanography, whose team estimated that expected economic damages from CO_2 emissions will range from $177 to $805 per metric ton of CO_2, with a median value of $417. The social cost of carbon (SCC) at $417/metric ton adds $3.71 to the cost per gallon from the health, climate, and other economic damages of the CO_2 emitted by burning a gallon of gasoline.[ii] However, it should be noted that the Ricke et al. (2018) values are based on constant 2005 dollars. Adjusting for the inflation rate between 2005 and 2020 would increase the social cost of carbon to ~$563 per ton of CO_2, or $5.00 per gallon of gasoline-equivalent in 2020 dollars.

EPA (2023) provides an updated range of estimates of the Social Cost of Greenhouse Gases more broadly, or SC-GHG, also including Methane (SC-CH_4) and Nitrous Oxide (SC-N_2O), as they might change over the years 2020-2080 (expressed in 2020 dollars).[iii] Depending on the year and the discount rate, the SC-CO_2 cost ranges from $120 to $600 per ton. One big question, of course, is how to turn those avoided costs (or benefits) into appropriate incentives that can further strengthen market alternatives favoring reduced carbon or carbon dioxide emissions.

III. Applying Bayesian Inference Techniques to Independently Assess the Cost Estimates for Ethanol Decarbonization

The remaining sections of this paper summarize the results of several independent analyses of the reasonableness of the costs for ethanol decarbonization as presented in the EFI Foundation report. Section IIIA explores how "experience curves" confirm or point to a likely reduced future cost of ethanol decarbonization (at least to some extent), as otherwise reported in the main narrative of this report. Section IIIB then introduces the idea of a "Monte Carlo Simulation" to confirm the likely magnitude of costs associated with that scale of decarbonization. Section IIIIC section provides brief working conclusions and prospective next steps forward while the last section, Section IV, provides a list of references used in the assessment that follows.

IIIA. Statistical Aspect One: The Experience Curve

While the main analysis suggests a hard cost of technology pathways ranging from numbers like $35 to $140 per ton of carbon dioxide emissions reduction (expressed in constant 2024 dollars), a combination of things like economies of scale, improved access to supply chains, and experience in building and putting critical technologies to work can lower the cost from, say, a high cost of $140 down to perhaps $35 or even less.[2]

One way to explore the potential for future cost improvements is to evaluate the scale of future cost reductions using what might be called an "experience curve." In other words, experience is gained as the volume of emission reduction technologies and their managed use or implementation increases over time. For example, Laitner and Sanstad (2004)

[2] Perhaps not immediately obvious to the reader but reducing the costs of decarbonization from a suggested range of $140, down to a much lower $35 per ton, means that yes, costs are coming down even as the social costs carbon (i.e., the growing climate burden) are likely to increase beyond $185 per ton in future years. Hence, there is a likely positive increase in any benefit-cost ratio which might complement the full set of findings within the main narrative.

characterized a series of 15 selected technologies and showed that the use of those technologies tended to reduce their cost at different rates as a function of their different levels of "experience" or the doubling in the individual use.[iv] As they documented, the "learning rates" of those different machines and devices ranged from a 4% reduction in cost for each in doubling the use of magnetic ballasts to 58% in doubling the use of integrated circuits. They noted, however, that the majority of technologies—whether electronic ballasts, the Ford Model T, or substitutes for chlorofluorocarbons (CFCs) —had learning rates that tended to range from a 15% to a 25% cost reduction for each doubling. In other words, each doubling of use was the "experience" with a given technology, and the associated reduction in cost was the "learning rate."

The basic formula for estimating the "learning rate," or LR, is a function of Cost at time t, or C_t, compared to the initial Cost in the first year, or C_0, but also as a function of the number of doublings, *Dbl*, in the use of a given technology, as shown in the equation below:

$$LR = 1 - \left(\frac{C_t}{C_0}\right)^{\left(\frac{1}{Dbl}\right)}$$

To show how this idea works and to explore a more recent example of cost reductions, an analysis documented here taps into both the Lazard (2024) cost trends for utility-scale solar photovoltaics (PV) and the scale of production as documented by the U.S. Energy Information Administration.[v] [vi] As Lazard suggests, for example, the cost of solar photovoltaic systems has dropped, in constant dollar values, from 36 cents per kilowatt-hour (kWh) in 2009 down to just 6 cents/kWh in 2023 as the scale of production saw a 7.53 rate of doubling of utility-scale PV (again in kWh), again over those same years.[3] Or:

$$LR = 1 - \left(\frac{\$0.06/kWh_t}{\$0.36/kWh_0}\right)^{\left(\frac{1}{7.53}\right)}$$

Thus, the learning rate, LR, is 0.212, given these assumptions. In other words, for each doubling of production, the cost has decreased by (1 – 0.212), 78.8% of its previous level.

[3] Without going into analytical detail here, with PV generation of 890,000 megawatt-hours, or MWh, in 2009 and a total output of 164,202,000 MWh in 2023, the implied number of doublings, or Dbl, is 7.53.

And we can then show how the cost in 2023 might be reduced from the rate documented in 2009 with the equation:

$$Cost_{2023} = \ Cost_{2009} * (1 - 0.212)^{7.53}$$

Or

$$Cost\ of\ \$0.36\ in\ 2009 * (1 - 0.212)^{7.53} = Cost\ of\ \$0.06\ in\ 2023$$

With this backdrop, we can then suggest how the "experience curves," together with the several different "learning rates," might impact future costs of ethanol decarbonization. Because there is no documented evidence of a fixed learning rate, nor can we be sure of the number of doublings in the next several decades that might be possible in the production and use of decarbonized ethanol, the table that follows highlights the range of possible cost reductions given learning rates of 12, 16, and 20% together with an array of 3, 6, 9, and even 15 doublings in the use of these new fuels.[4]

Table 1.

Exploring Cost Decreases as a Function of Production Doublings (Year 0 = Intial Scale of Use)				
Learning Rate		**12%**	**16%**	**20%**
Number of Doublings	3	0.681	0.593	0.512
	6	0.464	0.351	0.262
	9	0.316	0.208	0.134
	15	0.147	0.073	0.035

If the cost index in, say, 2027 (the initial year of production) is = 1.000, with a learning rate of 12%, together with decarbonized ethanol reaching a total of ~6 doublings by the year 2050, then the future cost in year 2050 can be estimated by the formula:

$$Cost_{2050} = \ (1 - 0.12)^{6} = \sim 0.464$$

[4] While there is not documented evidence of the potential scale of experience curves as they might be expected to lower future costs of ethanol decarbonization, the author did pull together some working analytics to suggest a reasonable range four to six doublings (perhaps more, depending on policy initiatives) with learning rates which might also fall within 12 to 20 percent (again, as a function of the scale of policy and market initiatives). Hence, the results summarized here are likely to be consistent with likely positive market outcomes.

or about 46.4% of the initial year or “Year 0” value. So, if the cost of carbon intensity reduction, as previously suggested, might be $140 per ton of carbon dioxide emissions in 2027 (expressed in constant 2024 $), then a six-fold doubling by 2050 implies a potential lower cost of $140 * 0.464, or $64.96/ton in that year (again expressed in constant 2024 $). Following the logic of the table, if the learning rate were as high as 20%, but with still 6 doublings, then the anticipated cost might be $140 * 0.262, or $36.68/ton in that year.

From an early production of perhaps 0.8 billion gallons of decarbonized ethanol in 2027, rising to perhaps 3.9 billion gallons in 2050, that implies a total cumulative production of 47.1 billion gallons by 2050 (assuming the share of decarbonized ethanol reaches 25% of total ethanol production by 2050), then we might anticipate about 5.87 doublings, or very close to the 6 doublings shown in Table 1.[5] One immediate takeaway from the “Experience Curve” data explored to this point is that the range of cost estimates, especially their combined use within different pathways and their resulting aggregated average costs, both high and low, appear to fall within the range of reasonableness. Perhaps more critically, the experience curve data also underscores the likelihood of future cost decreases as a function of both doublings and learning curves.

Some Further Perspectives We Might Explore

While we can point to some initial estimates of the various scales and costs of decarbonizing strategies, the question, of course, is how they meld into a combined final market cost and how they will also trend over time. And among the major drivers or market influences that might impact both the gamut of production outcomes and the possible rates of learning?

- Scale of the market potential. . . especially compared to alternative technologies. Is ethanol seen merely as a transition resource that can help pivot to a zero-carbon energy economy? Or will it be seen as a small but significant resource in

[5] The production data of 0.8 billion gallons assumes a small scale of production of decarbonized ethanol in 2027 which rises to about 25 percent of vehicle use of ethanol in 2050 and suggested in the main narrative, or 3.9 billion gallons. Summing that production over those same years yields a cumulative consumption of 47.1 billion gallons. The number of doublings is estimated as Ln(3.9 / 0.8) / Ln(2) = 5.87. If 47.1 billion gallons in 2050 seems like a lot, in 2022 alone, Americans used about 135.7 billion gallons of gasoline in just that one year alone. Most of the finished motor gasoline sold for vehicles in the U.S. is about 10% fuel ethanol by volume. See: https://www.eia.gov/energyexplained/gasoline/use-of-gasoline.php

2050. For example, former MIT materials scientist Dr. Saul Giffith (and a colleague who used my work as part of his book Electrify) suggests that ethanol may not be needed at all.[vii] At the same time, the IEA's Net-Zero 2050 report suggests that it might be an important but small-scale resource.[viii] It posits a 2050 global energy demand for liquid bioenergy of 15 exajoules, or about 2.8% of total primary energy needs in that year.

- Supply chain: the scale of development, possible competitions, and potential shortages, as they all might affect (limit or enhance) ethanol production.
- Economies of scale and scope. The previously cited Lazard (2024) underscores the importance of scale in maintaining lower costs in a number of ways.
- Ways of improving the rates of learning, whether by new innovations, accelerated research and development, workforce training, or improved supply chain management to improve those learning rates. As in the previous example, if the initial cost is $140, with a 12% learning rate and 6 doublings of production through 2050, then = $140 * $(1- 0.12)^6$ = $64.96 per ton. But again, if that learning rate can be boosted to 20% as data now suggests for utility-scale PV systems, then drawing on Table 1 coefficients suggests a potential future cost of $140 * 0.262 = $36.68/ton.
- Similar to hydrogen production, will the quantity of decarbonized ethanol produced be potentially greater than end-use consumption technologies might be able to fully absorb? In short, how much can the economy actually consume compared to what might otherwise be produced?
- Will the big producers affect or limit other emerging markets or technologies?
- How might the parasitic aspects of the materials needed, as well as other energy and water requirements used in the construction and operation of the different technology pathways, impact the scale and production of decarbonized ethanol?
- Given the various programs, policies, and workforce training initiatives that might enable a greater scale of production, what might that add to the overall cost? And how might all of that, in turn, affect production and consumption patterns?
- Will non-energy benefits and the avoided social costs of carbon (SCC) positively impact the production and use? As noted, Rennert et al. (2022) found that every

additional ton of carbon dioxide emitted into the atmosphere costs society $185. As they note, this is far higher than the federal estimate of $51 per ton at that time. Does an avoided $185 of damage become a benefit that encourages investment in low-carbon ethanol?

- From a related perspective, if we imagine climate change as an "economic damage function," how will that impact markets and economic resilience? Researchers from the Potsdam Institute (Kotz et al. 2024) suggest that North American GDP may be eroded by about 11% by 2050.[ix] [6] Without getting into too much detail but building on the EIA's Annual Energy Outlook 2023, this suggests an impact of ~$4.9 trillion (2024$) in 2050. Seen in that light, decarbonized ethanol might become an important part of the solution.
- Will demand-side options such as greater fuel economy, shared mobility, and/or greater freight and transit options affect production?
- Might we introduce the idea of "opportunity cost," which suggests that if we go one pathway, we will get X set of benefits, but if we go a different pathway altogether, we'll get perhaps more like 1.5X or 2.0X the benefits? And finally. . .
- In the spirit of a favorite 1982 Stanford University journal article, this information and the set of questions posed are all highlighted as we are "modeling more for insights than absolute precision."[x]

IIIB. Statistical Aspect Two: A Monte Carlo Simulation

With an understanding that different learning rates and scale of manufacturing can improve overall costs in the production of decarbonized ethanol, we can turn to Monte Carlo simulations to provide yet another array of prospective outcomes on the costs of those possible outcomes. Monte Carlo simulations belong to a class of computational algorithms that rely on repeated random sampling to estimate their outcomes. Such methods are often used when replicating physical and mathematical systems and when data are incomplete.

[6] While I have briefly reviewed this report, and I am in communication with the lead researcher of the Potsdam Institute, I need to do some further review and confirm the 11 percent figure for the U.S. economy. But it is on that scale for North America, and perhaps as much as 19 percent damages for the Global economy.

Hence, Monte Carlo methods are especially useful for modeling phenomena with significant uncertainty in assumptions or inputs. This might include calculating different capital costs (Capex) or operating costs (Opex) together with the financial implications of different debt and equity shares necessary to underwrite the investment magnitudes. It also includes the returns on those investments, given the debt and equity shares.

The most famous early use of this type of simulation was by Enrico Fermi, who, in 1930, used a random method to calculate the properties of the newly discovered neutron. Monte Carlo methods were central to the simulations required for the Manhattan Project, though they were severely limited by the computational tools available at the time. Therefore, only after electronic computers were first built (from 1945 on), Monte Carlo methods began to be studied in depth.

Here we rely on Monte Carlo simulations using triangular distributions in which we assume a reasonable or most likely value of a given variable. As already noted, this might reflect the range of Capex and Opex needed to produce an assortment of decarbonization techniques and reduction in carbon intensities. To that extent, then, we rely on existing data reported in the main narrative to estimate a minimum and maximum likely set of values that might be taken as the largest (most costly) and smallest available data points (least costly).

The Monte Carlo technique then generates a set of random numbers to more easily explore the interactions among the many different variables and their very large uncertainties. In this regard, we stress that most of the distributions utilized here were assumed, and thus, probabilistic results should be taken as approximate.[7] Yet, as we shall find, the overall results fit intuitively within the expected pattern of other concrete savings estimates (within their contribution to the larger economy) and with other studies that have been undertaken with a more limited scope.

While there is no single Monte Carlo method or pre-determined set of algorithms that might be applied in any given context or market scenario, the table that follows highlights the assumptions used here.

[7] A working perspective of the Monte Carlo technique can be found in an investment writeup by Will Kenton (updated June 27, 2024), at https://www.investopedia.com/terms/m/montecarlosimulation.asp.

Table 2.

Range of Monte Carlo Variables and Metrics ($/Tonne CO_2 Reduced)							
Key Variables	**Source**	**Low**	**Mid**	**High**	**MC - Low**	**MC - High**	**MC Result**
Total Capital Costs ($/Tonne Equiv)	Rnd	-$100	$80	$120	-$64	$94	-$36
Debt Share (Percent)	Rnd	20%	35%	60%	21%	48%	34%
Debt Cost (Percent Return)	Rnd	3%	5%	7%	4%	6%	5%
Equity Share (Percent Capital)	Calc	80%	65%	40%	79%	52%	66%
Equity Gains (Percent Return)	Rnd	7%	11%	15%	11%	15%	13%
Weightd Average Return (Percent)	Calc	6.20%	8.90%	10.20%	9.53%	10.68%	10.28%
Estimated Technology Life (Years)	Firm	20	20	20	20	20	20
Uniform Capital Recovery Rate	Calc	8.9%	10.9%	11.9%	11.37%	12.30%	11.97%
Levelized Capital Cost ($/Tonne)	Calc	-$8.86	$8.70	$14.29	-$7.28	$11.56	-$4.31
Total Opex ($/Tonne)	Rnd	$24	$30	$53	$24	$44	$32
Total Annual Cost ($/Tonne)	Calc	$15.14	$38.70	$67.29	$16.72	$55.56	**$27.69**

The rows of Table 2 refer to the specific variables used within the simulations, including Capex as underpinned by different shares and returns of debt and equity, together with the expectation of investment returns associated with a given mix of investment patterns. A critical row shows Capex as amortized into “Levelized Capital Cost” or costs, to which we then add Opex, which generates a bottom row estimate of "Annual Cost per Ton." The "Source" column references how each row uses random variables ("Rnd"), a calculation based on prior random variables ("Calc"), and the assumed hard value, which provides the estimated life of any given assumed technology ("Firm").

Also in Table 2, a fixed range of "Low", "Mid", and "High" estimates are reported for the different variables. But then "MC - Low" (not “marginal cost” but Monte Carlo - Low) generates a random value from an assumed "Low" and "Mid." As then expected, the "MC - High" (or Monte Carlo - High) generates a random value from an assumed "Mid" to "High" end. This enables an asymmetric array of variables, which, as now listed, tends more to the higher-end cost range. With the full mix of MC – Low, together with the MC - High, a final randomly assigned value of "MC Result." All of this generates a final random value of "Total Annual Cost /Ton" which becomes one of a thousand random final costs per ton. This is reported here as the bold green text in the bottom right corner of Table 2.

As shown in the first row, with an assumption of capital costs (Capex) that might range from a $100 savings (shown as -$100) to perhaps a high of $120 per ton, a random amount might result in a cost of -$36 per ton (last column in the first data row). Then, given the range of other uncertainties – including the shares and the returns on both debt and equity, together with an operating cost (Opex) of $32 per ton, the weighted costs might be $27.69/ton equivalent for at least one iteration or run of the model (again the bold green text of the bottom right corner).

Given this array of assumptions and random variables, the simulation is run 1,000 times to accommodate the full array of different outcomes and then aggregates a far-ranging average of the many different but likely outcomes. Table 3 shows a final set of results based on those 1,000 iterations.

Table 3.

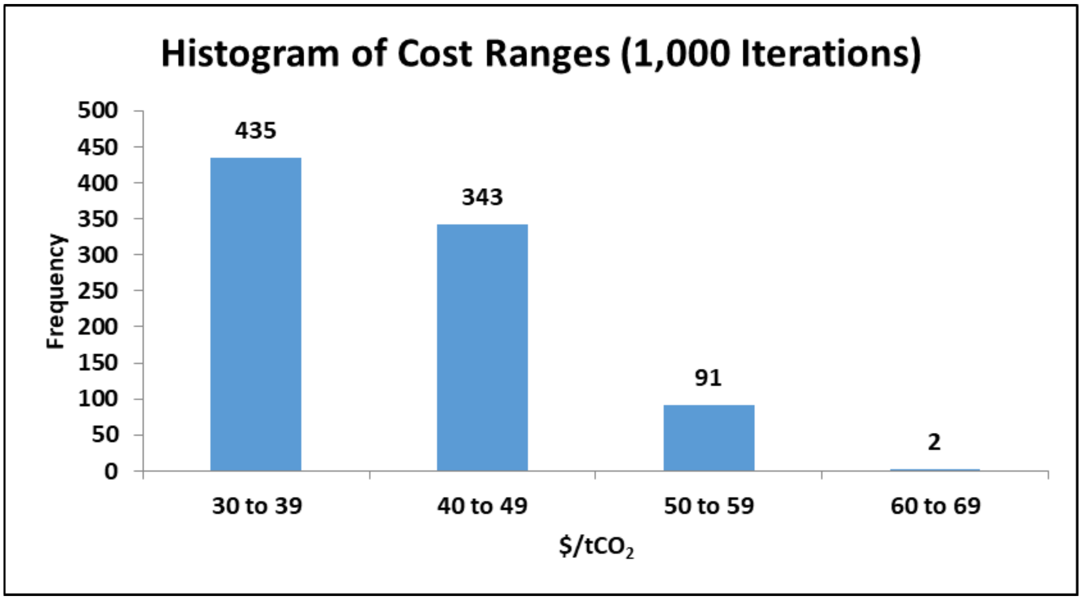
Monte Carlo Results (1,000 Iterations)	
Metric	**Cost $/tCO$_2$**
Minimum Cost	**16.63**
Maximum Cost	**62.58**
A Very Average Cost	**39.13**
Standard Deviation	**7.89**
95% Confidence Interval - Low	**23.67**
95% Confidence Interval - High	**54.59**

In short, with the wide range of potential Capex and Opex costs, together with an assortment of possible returns on investment, as shown in the table above, the simulation suggests an array of total costs that span a low of $16.63 to a high of $ 62.58, with an average cost of $39.13 per ton. At the same time, it appears that ~95% of the iterations might fall within $23.67 to $54.59 per ton. This appears to confirm, well within an order of magnitude, the cost estimates reported in the main narrative of this analysis.[8]

Given all this, we then generate a "Histogram of Cost Ranges" based on 1,000 iterations, as summarized in Figure 1.

[8] As a further confirmation of findings, to choose another independent study of scale and cost of ethanol decarbonization, see Dees, John, Kafayat Oke, Hannah Goldstein, Sean T. McCoy, Daniel L. Sanchez, A. J. Simon, and Wenqin Li. “Cost and Life Cycle Emissions of Ethanol Produced with an Oxyfuel Boiler and Carbon Capture and Storage.” Environmental Science & Technology 57, no. 13 (April 4, 2023): 5391–5403. https://doi.org/10.1021/acs.est.2c04784, which suggests decarbonization on the scale of $52 to $84 per ton CO_2e for just one pathway, the “Ethanol Produced with an Oxyfuel Boiler and Carbon Capture and Storage.”

Figure 1.



The results in Figure 1 show that, although there may be very high or very low average annual costs, despite the array of uncertainties in costs and financial underpinning the end result, suggests that the frequencies of costs tend to confirm a strong likelihood in the range of \$30 to \$49 per ton. While Figure 1 provides an average of aggregate technology pathway costs, these averages appear consistent with the findings highlighted in the main report.

IIIC. Some Concluding Thoughts and Possible Next Steps Forward

In the spirit of what we referred to as Bayesian inference, the application of both Experience Curves and Monte Carlo simulations appears to confirm the assessment of “A Strategic Roadmap for Decarbonizing the U.S. Ethanol Industry” – with a very real possibility of actually seeing lower costs per ton than might be shown as a function of the different pathways previously described. But in this section, we explore the likelihood of similar or improved, perhaps an even better set of outcomes than posed by the main narrative and analysis. While Bayesian inference is seen as an important technique in statistics, the updating can provide an important aspect in the analysis of the ethanol story. At the same time, there are circumstances and market conditions that may impact the key findings of the main narrative. As perhaps a next step forward, we may want to explore not only the costs but also the benefits as mentioned in Section II. Finally, as discussed in Section III, there is evidence to suggest there are many different market conditions and outcomes that may affect the results shown here. Hence, there is a need for possible forward-looking policies, programs, and incentives that can more likely ensure a more positive economic outcome that underpins both the production and use of decarbonized ethanol.

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