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Spotlight Statement

Rising electric vehicle (EV) adoption is accelerating the shift away from petroleum-derived fuels. Together with increasingly stringent carbon pricing, this trend challenges the refining sector by raising questions about whether refineries can remain profitable under uncertain fuel demand while meeting tighter emissions targets. This study examines how fuel demand shifts affect greenhouse gas (GHG) emissions, the cost-effectiveness of carbon capture in the U.S. refining sector, and refinery responses to market and policy change. Our findings suggest that CCS may function either as a transitional mitigation strategy or as a means of extending refinery operating lifetimes, depending on the timing and strength of market and policy signals. Policy must therefore balance supply security with long-term decarbonization.

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ARTICLE

Analysis of Carbon Capture Strategies for Refineries Considering Extraordinary Future Economic and Policy Uncertainties

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The shifting transportation landscape, driven primarily by the electrification of the vehicle fleet and tightening carbon regulations, is reshaping the market for liquid fuels and challenging many existing refineries. Strategic decisions about carbon mitigation investments, such as carbon capture and storage (CCS), are complicated by uncertainty in evolving fuel markets and regulatory frameworks. This study assesses the cost-effectiveness and the opportunity of deploying CCS within the refining sector in the United States amidst a transitioning transportation fuel market and increasingly stringent carbon pricing policies. By integrating a carbon capture module into the Petroleum Refinery Life Cycle Inventory Model (PRELIM), we assess greenhouse gas (GHG) emissions under various fuel demand scenarios and examine the role of CCS in mitigation. Our findings indicate that the annual GHG emissions from U.S. refineries may decline from 212 $MtCO_2/y$ in 2019 to 111 $MtCO_2/y$ in 2050 due to demand shifts, while CCS could further reduce emissions to 47.6 $MtCO_2/y$. Fluid Catalytic Crackers (FCCs) are the most significant emissions source, with a potential reduction of 18.5 $MtCO_2/y$ at a CO_2 avoidance cost as low as $83.5/t. We also conduct a real options (RO) analysis to explore how refineries might respond to fuel market changes and carbon pricing. Results suggest hydroskimming refineries could be phased out by the early 2030s due to market and policy pressures, while medium and deep conversion refineries may accelerate CCS deployment by the 2040s. Hence, policy should enable CCS deployment as a transitional mitigation strategy while maintaining consistency with long-term decarbonization pathways.

Introduction

Petroleum refineries convert crude oil into different high-value products (e.g., gasoline, diesel, jet fuel, fuel oil) that fuel the economy today. For example, energy sourced from petroleum contributed 38% (37.3 Exajoules) of total primary energy consumed in the U.S. in 2023, with most (i.e., ~70%) being consumed by the transportation sector.[1] The refining sector is also the third largest greenhouse gas (GHG) emitting industry globally, accounting for 6% of global GHG emissions.[2] Efforts to restrict global temperature rise to a maximum of 1.5 ^oC above pre-industrial levels,[3] have created unprecedented pressure on refineries to remain economically competitive while simultaneously reducing their carbon footprint, adapting to dynamic shifts in demand for their products and input crude supply options. As an example, according to the National Renewable Energy Laboratory (NREL)'s Electrification Future Study (EFS),[4] the demand for gasoline in U.S. could drop from ~19.7 Gigajoules per year (GJ/y) in 2019 to a range of about ~3.97 to ~15.6 GJ/y depending on the extent of personal vehicle fleet electrification (i.e., electric vehicles gaining market share over internal combustion engines). Another example is that crude quality (e.g., API gravity and sulfur content) fluctuates based on refiners' access to cheaper crudes and their ability to process these crudes into preferred products, and this creates uncertainties in decarbonizing the refining sector.[5] At the same time, the U.S. have pursued policies aimed at reducing GHG emissions, with ambitions varying across administrations.[6–8] The timing and stringency of current and potential future climate policies create unprecedented uncertainty as refiners, as well as the sectors upstream and downstream in the supply chain, make critical decisions over the next decade.[9]

The strategies that refineries could employ to respond to these pressures and their consequences are complex. Refiners can change their operations (e.g., change the flows of crude fractions between different process units) to adapt to changes in product demand and crude quality changes.[10] For instance, if there is a shift towards heavier crude in the market, a refiner could react in a few different ways. One option would be to simply process crude with a lower average API gravity. This would result in reduced naphtha yield from the atmospheric distillation tower (AT) and thereby decrease the volume of gasoline produced. This is fine if there is a corresponding decrease in demand for gasoline. However, if demand for gasoline remains constant and capacity permits, the refiner could change the operating conditions of the AT and vacuum distillation unit (VDU) to direct more atmospheric gas oil (AGO) and vacuum gas oil (VGO) (which tends to be more plentiful in

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heavier crude oil) to the fluid catalytic cracking (FCC) unit, thus maintaining overall gasoline output and maximize the refinery profit.[11] In the case where the demand for transportation fuels, such as gasoline, declines while the demand for other products does not drop proportionally, refiners could direct the naphtha fraction from different process units (e.g., AT, Coker, FCC, etc.) towards alternative uses, such as steam cracking for petrochemical feedstock production.[12] Alternatively, refiners could also lower overall crude consumption and therefore their production to respond to the declining demand. However, lowering the utilization rate could reduce the refinery's efficiency and make it less competitive with other refineries in the market, and could ultimately lead to a complete shutdown.[13] These potential future conditions and reactions at an individual refinery will not only affect their profitability, they will also change the refinery's overall emissions profile[10]. Beyond operational changes, refineries might also consider new investments to reduce GHG emissions in the face of new and increasingly stringent environmental regulations.[13] In the case of a stricter carbon pricing scenario, refiners could reduce their carbon footprint by implementing mitigation measures, such as carbon capture and storage (CCS) to lessen the financial impact of carbon pricing on refinery margins. CCS has been widely discussed as a promising emissions mitigation solution despite substantial financial commitment.[14–20] However, the CO_2 formed throughout the refinery is dispersed and exhibits heterogeneity in terms of volume and CO_2 concentration. This results in considerable variability in both emissions reduction potential and the cost of carbon capture.[21,22] Moreover, the decision to invest in carbon capture technology within a refinery is not only influenced by the costs associated with its implementation but also by the uncertainties due to a dynamic fuel market and future climate policy stringency. Climate policies are also subject to frequent and difficult to predict changes driven by government and public opinion, momentum of international negotiations, changing technology landscape, and global progress towards emissions reduction targets.[23]

Given the simultaneous challenges of navigating a dynamic fuel market and uncertain carbon policies, refiners face a great deal of risk when faced with emissions reduction decisions, such as implementing CCS which requires a high upfront capital investment. Current literature often examines the decarbonization pathways by considering one or a small number of uncertainties, but typically without fully accounting for their combined influence. For example, Young et al.[24] and Sun et al.[20] evaluated the GHG emissions reduction for U.S. refining sector under contemporary market conditions (i.e., 2017 & 2023), but did not account for future fuel market dynamics. Similarly, Kim[10] evaluated the role that refinery changes can play in affecting emissions reduction potential in an uncertain future; however, other potential responses, such as refinery shutdowns, in the face of future uncertainties were not considered. Hence, this research bridges the gap in existing literature by considering the influences of multiple factors in a consistent way, including potential shifts in the transportation fuel market as the economy transitions towards decarbonization, timing and stringency of carbon pricing, and their combined effects on U.S. refinery GHG emissions and strategic decision-making.

To fill the above knowledge gap, this study seeks to accomplish three objectives. First, we investigate how uncertainties in future refinery product demand at the regional level (Petroleum Administration for Defense Districts, PADD)—driven by factors such as the rate of decline in gasoline demand due to the increasing penetration of electric vehicles (EVs)—could significantly affect U.S. refinery GHG emissions. Second, we examine the distribution of CO_2 avoidance costs across different process units, refinery configurations, and PADD regions to understand the economic feasibility of carbon capture, as well as its implications for investment prioritization and policy design. Third, we use real option (RO) analysis, investigate the potential impact of selected actions (i.e., continue operating refineries without abating emissions, deploying a carbon capture unit within the refinery, shut down the refinery) that different refinery archetypes (i.e., a "typical" refinery of different types) might take when uncertainties about market conditions and climate policy stringency are considered. This study offers insights into how different refinery types may respond to a number of changing future conditions and uncertainty, helping refiners make informed decisions and highlighting where policy may be needed to achieve outcomes that individual refineries might not pursue on their own.

Methods

PRELIM and Carbon Capture Module

Petroleum Refinery Life Cycle Inventory Model (PRELIM) is an Excel spreadsheet-based life cycle inventory model to evaluate the gate-to-gate environmental impacts of refineries' operations. The model inputs include specifications of crude assays such as the American Petroleum Institute gravity (API gravity) and sulfur content, refinery configurations (i.e., the different combinations of process units) and product slates (i.e., the composition of refinery products). A carbon capture module is integrated within PRELIM to explore both the emissions reduction potential and the economic performance of implementing carbon capture technologies in refineries (ESI†, Figure S1).

PRELIM considers a total of 7 different combinations of process units (i.e., configuration) for petroleum refineries (ESI†, Table S1), with the addition of a carbon capture and a compression & dehydration unit in the carbon capture module. It also accounts for four types of utilities - electricity, heat, steam, and hydrogen - that drive refinery operations. GHG emissions from the refinery operations are estimated by applying emissions factors to the total utilities consumed. The strategy employed in the carbon capture module is post-combustion with a many to one setup (i.e., individual absorbers are assigned to each furnace with a common regenerator). Oxy-fuel combustion is also modeled in the carbon capture module because it is anticipated to be a potentially less costly option for FCC units.[25] However, it is not utilized in this study because it has not yet been commercially implemented on FCC units. Additionally, employing oxy-fuel combustion for the FCC and post-combustion on other units would reduce the economy-of-scale benefit of the many-to-one model. Steam and electricity consumption, due to absorbent regeneration and fluid circulation, is calculated based on CO_2 concentration in flue gas. The specific steam consumption (i.e., MJ steam/kg CO_2) uses literature-averaged values for various flue gas flows [26–32], while specific electricity consumption (MJ electricity/kg CO_2) is determined by a literature-based correlation. [27] The carbon capture module assumes a multi-stage centrifugal CO_2 compression with inter-stage cooling for dehydration. Detailed information could be found in Supplementary Method 2 (ESI†).

Transportation Fuel Demand and Refinery Product Slate

This study uses the 2019 transportation fuel demand in the U.S. as a baseline, as documented by the Energy Information Agency (EIA).[33] The EIA's production data for refinery products at the regional level[34] are used to define the 2019 PADD-level product slates, which are used to set the target output of PRELIM. The model optimizes refinery operations to achieve that product slates in each PADD. Transportation fuel consumption is assumed using the projections from EFS, which estimate demand from 2017 to 2050 under different EV adoption scenarios in each PADD. To illustrate the impact of potential changes in fuel consumption, two specific years - 2035 and 2050 - have been selected as timestamps. To translate the projected transportation fuel consumption in these years to refinery products slates, the proportion of the refinery product that is transportation fuel (see Table S2, ESI†) as well as the proportion of transportation fuel produced within the PADD (see Table S3, ESI†) are held at historical averages according to EIA data.[1,35–38] While we know that these proportions will also change in the future, how they will change is highly uncertain and forecasting these dynamics is outside the scope of current work. A detailed procedure for generating refinery product slates is outlined in ESI† (Supplementary Method 2).

Crude Qualities and Crude Proxies

The 2019 crude qualities[5] (i.e., API gravity and sulfur content) for different PADDs as well as the volume of crudes assays imported from different country for individual refineries[39] in the U.S. are documented by EIA and thus will be used to blend the crude proxies based on the volume proportion of each crude assay. Future crude quality in each PADD is represented using a set of bounded shifts in API gravity and sulfur content relative to the 2019 baseline.[5] We define two paired scenarios: light versus heavy crude with respect to API gravity, and sweet versus sour crude with respect to sulfur content, to evaluate potential differences in refining-sector GHG emissions. In the light scenario, API gravity is assumed to be higher than the 2019 baseline, whereas in the heavy scenario it is lower. Similarly, sulfur content is assumed to be lower than the baseline in the sweet scenario and higher in the sour scenario. The magnitude of these deviations increases over time, such that changes in the near term (e.g., 2035) are smaller than those in the longer term (e.g., 2050) (ESI†, Table S4 and Figure S2). These stylized ranges are intended to span plausible conditions above and below present-day averages and to provide long-term inputs for scenario analysis, rather than to predict specific crude slates processed in U.S. refineries. The wider range considered for 2050 reflects the longer adjustment period over which larger shifts in crude quality could occur, recognizing that actual future crude composition will depend on supply-side, geopolitical, and resource depletion dynamics not explicitly modeled here. A crude proxy is then blended, using the approach developed by Cooney et al.,[40] with domestic crudes and the top 10 imported crudes in each PADD to achieve the projected API gravity & sulfur content. A detailed procedure for projecting future crude qualities and blending crude proxies is presented in ESI† (Supplementary Method 2).

Refinery Throughput

This study applies an approach developed by Kim[10], which adjusts the configuration level crude throughput to minimize the difference between the multi-linear regression model-derived regional Standardized Refinery Complexity Index (SRCI) and the volume-weighted regional SRCI under multiple constraints. The individual refinery's SRCI is originated from the Nelson Complexity Index (NCI) and is able to rank refineries based on their complexity, considering secondary conversion capacity and unit complexity[41–43]. Similar to NCI, higher SRCIs indicate a refinery's ability to process heavier crude and produce high-value products like gasoline and diesel. The configurational SRCI consolidates individual refineries' SRCI using their volume shares of crude throughput among refineries with the same configuration in each PADD from 1999 to 2019 (ESI†, Table S5). Regional SRCI is the volume-weighted average of configurational SRCI, which offers a standardized metric for assessing and comparing regional refinery complexity. Using a multi-linear regression model (equation (1) and (2)), refineries can estimate regional volume-weighted SRCI based on API gravity, gasoline, diesel, and jet yields (data collected from the EIA[5,44] and OGJ[45]). Table S6 (ESI†) summarizes coefficients for the multi-linear regression model. This allows refineries to project future regional SRCI, helping them assess the complexity required for future crudes and product slates to meet market demands. A detailed procedure to estimate the refinery throughput is presented in ESI† (Supplementary Method 2).

$$SRCI_i^{Target} = a_1 \times API_i + a_2 \times Gas_i + a_3 \times Diesel_i + a_4 \times Jet_i \tag{1}$$

$$SRCI_i^{VWAP} = \sum_{j=0}^{6}\left[SRCI_{Config,\,i} \times \left(\frac{x_{j,i}}{\sum_{j=0}^{6} x_{j,i}}\right)\right] \tag{2}$$

The objective function thus could be expressed as shown in equation (3) and is optimized using MATLAB's fmincon solver.

$$Minimize\colon f_0(x) = |SRCI_i^{Target} - SRCI_i^{VWAP}| \tag{3}$$

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Where i denotes the PADD number, j denotes the refinery configuration, a_1, a_2, a_3, a_4 are the regression coefficients, $SRCI_i^{Target}$ is the multi-linear regression modelled target Standardized Refinery Complexity Index, $SRCI_i^{VWAP}$ is the regional volume-weighted Standardized Refinery Complexity Index, $SRCI_{Config,\,i}$ is the configurational Standardized Refinery Complexity Index, x is the crude throughput for each refinery configuration in each PADD, API is the regional crude input API gravity, Gas, $Diesel$, Jet are the regional gasoline yields, diesel yields and jet yields respectively.

It is important to note that the SRCI framework is calibrated using historical refinery data reflecting a transportation fuels - oriented operating regime. As such, it summarizes observed historical relationships rather than serving as a predictive tool for fundamentally different future operating conditions. Structural shifts in refinery configuration, product slates, or decarbonization strategies may fall outside the historical range on which the framework is based, and these transitions would not be fully captured without model adaptation and additional data to support validation under emerging operating paradigms. A detailed explanation is presented in ESI† (Supplementary Method 2).

CO_2 Avoidance Cost

The CO_2 avoidance cost, defined as the ratio of the annualized cost, including capital and operating expenditures, of implementing carbon capture, transport and storage to the annual amount of CO_2 avoided (the CO_2 stored that would have ended up in the atmosphere without CCS), allows refiners contemplating investments in mitigation (such as CCS) to make comparisons between options. The method of avoiding the cost of carbon capture is adopted from Gale et al.[21] and is shown in equation (4). Since the new-built refinery with carbon capture is not considered in this study, the selection of equation (4) is thus rational because it is suited for retrofitting carbon capture in existing facilities, according to Roussanaly et al.[22]

$$CO_2\ Avoidance\ cost = \frac{Annulized\ CapEx + Annulized\ OpEx}{GHG_{NoCC} - GHG_{CC}} = \frac{CapEx \times \frac{\mu(1+\mu)^n}{((1+\mu)^n - 1)} + Annulized\ OpEx}{GHG_{NoCC} - GHG_{CC}} \quad (4)$$

Where *CC* denotes the scenario with carbon capture deployed on certain process units, *NoCC* denotes the scenarios with no carbon capture deployed on certain process units, *CapEx* refers to the capital expenditure of the carbon capture facility, *OpEx* refers to the operating expenditure, μ is the discount rate, *n* is the lifespan of the carbon capture facility, *GHG* refers to the GHG emissions of the refinery.

Emissions from refineries, with or without carbon capture, are calculated using PRELIM and its integrated carbon capture module. In this study, we evaluated a total of 35 carbon capture scenarios on different process units for each configuration in different PADDs (ESI†, Supplementary Method 1). This module also enables the estimation of annualized costs through a bottom-up analysis that considers both CapEx and OpEx of the carbon capture unit. CapEx estimation includes the costs of essential equipment, construction, engineering, procurement, and construction (EPC) service costs, as well as others (e.g., owner's cost, spare parts cost, etc.). Some assumed parameters for estimating CapEx can be found in Table S7 (ESI†). Notably, all costs are adjusted to the year 2019.

OpEx encompasses annual fixed and variable operation and maintenance (O&M) costs and assumed parameters can be found in Table S8 (ESI†). Notably, this calculation of OpEx does not consider the potential cost implications of a carbon price, nor does it consider the sales of captured CO_2 as a commodity.

The costs associated with CO_2 transportation and storage are included in this study. However, a rather simple approach is taken due to the lack of scenario design for future CO_2 infrastructure and storage sites. Such a design would necessitate a rigorous analysis of future CO_2 transportation pipeline and storage site networks, which is beyond the scope of this study. Instead, we assume a preliminary case study, where CO_2 transport and storage costs are parameterized using a representative case and applied uniformly across regions to provide order-of-magnitude estimates for long-term strategic analysis. Specifically, we use the Scalable Infrastructure Model for Carbon Capture and Storage (SimCCS)[46] platform to generate an approximate cost for CO_2 transportation and storage in the Southeastern U.S. The estimated costs for CO_2 transportation were $6.31/t for capturing 100 $MtCO_2$/y. Similarly, the estimated costs for CO_2 storage were $4.37/t for capturing 100 $MtCO_2$/y. The potential estimated CO_2 leakage rate could range between 11.3 – 173 kt CO_2/y, based on parameters (e.g., failure rate, leakage occurrences, pipeline length, etc.) documented by Onyebuchi et al.[47] and Jensen et al.[48] In this study, we estimate an average of a total of 75.6 kt CO_2/y, which accounts for 0.0756% of total CO_2 storage rate (i.e., 100 $MtCO_2$/y).

A detailed description of the procedure for estimating the CO_2 avoidance cost is summarized in ESI† (Supplementary Method 2).

Real Option Analysis

While the CO_2 avoidance cost indicates the minimum carbon price needed to justify deploying carbon capture, it does not fully capture the complexities and uncertainties in market conditions and carbon pricing that refineries face. In contrast, RO analysis is able to account for the managerial flexibility required to adapt and revise later decisions in response to uncertain market developments[49], thus being a valuable tool for informing investment decisions for refiners. This study applies a binomial lattice tree model[50,51] to evaluate the potential strategic options the refiner might consider when facing an uncertain carbon price. Three individual refinery archetypes with different configurations, which are hydroskimming, "medium conversion: FCC & Gas oil hydrocracker (GOHC)" and "deep conversion: FCC & GOHC" refineries are considered in the RO analysis. These refinery archetypes could choose between three strategic options, which are 1) to continue operating the refinery without emissions abatement (i.e., "continue operation"); 2) deploy carbon capture in one or multiple process units (i.e., "deploy carbon capture"); and 3) shut down the refinery entirely (i.e., "shutdown refinery"). These options are evaluated over a 31-year timeline, providing refiners the opportunity to make decisions at each annual interval from 2019 to 2050, consistent with the flexibility of an American option. It should also be noted that PRELIM specifically models the crude throughput, product slates, and GHG emissions for selected benchmark years - 2019, 2035, and 2050. For the intervening years not directly modeled by PRELIM, it is assumed that changes in crude throughput, product slates, and GHG emissions occur linearly on a yearly basis. The underlying asset value of each refinery will be determined using the present value of future discounted cash flow (DCF), which will be initially determined based on projected prices of crude oil, refinery products, and utilities, as forecasted in the Annual Energy Outlook (AEO) by the EIA[52] and discounted by a rate of 12%. Carbon prices are assumed to follow a stochastic process (geometric Brownian motion, GBM). The uncertainty associated with prices in this model is handled by adopting a hybrid approach in which carbon prices are modeled stochastically while other uncertain variables (i.e., crude, fuel and utility prices) are examined through scenario analysis. This structure isolates the option value associated with carbon price uncertainty (the focus of this study), while avoiding the need to specify a fully parameterized joint stochastic process for multiple price variables that are strongly correlated in practice and could otherwise lead to overstated uncertainty if modeled independently. For a specified carbon price trajectory, a single binomial lattice is constructed and the expected present value at each node is determined using backward induction[51]. The optimal response is selected as the option that achieves the highest expected present value among the three possible responses (see Supplementary Method 3, ESI†). The expected present value of the shutdown response is set to 0 and is chosen if the expected present values for both continuing operations and deploying carbon capture are negative. Risk-neutral probability and backward induction are utilized to calculate each node's expected present value and corresponding options, where the risk-free interest rate is set as 2.40%, the average U.S. 20-year treasury bond rate in 2019.[53] A 12% discount rate is used only to compute the initial underlying asset value as the present value of future cash flows, representing the company's perspective on the project's economics based on the perfect foresight of future price projections. This risk-adjusted discount rate is not applied during the backward induction stage of the real-options analysis, because the project's risk profile becomes endogenous to the investment timing decision and may differ across options. A detailed explanation of this rationale is provided in Supplementary Method 3 in the ESI†. Monte Carlo simulation is then utilized for each lattice for 10,000 runs to illustrate the likelihood (frequency) of choosing different options that should be taken in different years. The Real Options model and Monte Carlo simulations are implemented in Microsoft Excel using Visual Basic for Applications (VBA). We

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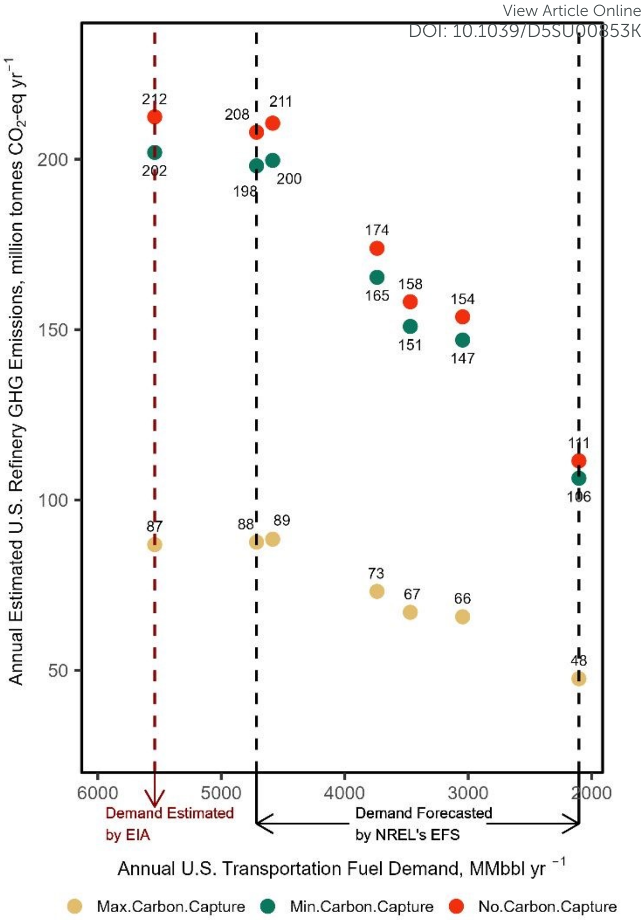

Figure 1. Estimated Annual GHG Emissions from U.S. Refineries at different transportation fuel demand with and without carbon capture. No carbon capture refers to the case that no carbon capture unit is deployed to any processes in the refinery. Minimum carbon capture implementation refers to the case where monoethanolamine-based (MEA-based) post-combustion carbon capture units are deployed on all FCC regenerators in U.S. refineries. Maximum carbon capture refers to the case where MEA-based post-combustion carbon capture units are deployed on all process furnaces/boilers as well as FCC regenerators in U.S. refineries. Red dashed vertical line refers to the volume (i.e., 5.54 Gbbl/y) of transportation fuel (i.e., gasoline, jet fuel, diesel, fuel oil) supplied to U.S. market in 2019. X-axis values correspond to those dots within the two vertical black dashed line are estimated volume (2.10 to 4.71 Gbbl/y) of transportation fuel demand using NREL's EFS data.

also construct two alternative stepwise carbon price trajectories - one with earlier increases and one with delayed increases - to assess the effect of timing on refinery decision-making under uncertainty. Detailed information on implementing the RO analysis is presented in Supplementary Method 3 in ESI†. Detailed information on each individual refinery is provided in Table S9 in ESI†.

Results and Discussion

U.S. Refining Sector Emissions under Different Carbon Capture and Transportation Fuel Demand Scenarios

Figure 1 shows possible changes in GHG emissions from the U.S. refining sector under various scenarios for future transportation

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fuel demand, market shifts in crude quality and application of carbon capture technologies. NREL's EFS are used to explore the impact of EV adoption in the U.S. on fuel demand and in turn, the impact on refinery GHG emissions. For example, the High Electrification scenario in EFS[4] (referred to in this study as an LD or low petroleum fuel demand) projected a decline in U.S. transportation fuel demand from 5.54 to 3.47 Giga barrels per year (Gbbl/y) from 2019 to 2035 and 2.10 Gbbl/y by 2050. We hereby categorize future fuel demands projected by EFS as LD, MD (i.e., medium petroleum fuel demand) and HD (i.e., high petroleum fuel demand) scenarios for different years (i.e., 2035 and 2050), as shown in Table 1. The two black-dashed vertical lines in Figure 1 show the bounds of possible demand in 2035 and 2060 across all the EFS cases. The 2019 fuel demand estimated by the EIA is used as the baseline petroleum fuel demand (BL) and is indicated by the red-dashed vertical line in Figure 1. All scenarios and their corresponding fuel demands are summarized in Table 1, with further details on the EFS provided in Table S10 (ESI†).

Changes in fuel demand will directly impact refinery production levels and, consequently, crude input requirements (See Methods). For example, under the LD scenario, total annual production from U.S. refineries is estimated to decline from 7.20 Gbbl/y in 2019 to 5.32 Gbbl/y in 2035 and further to 3.69 Gbbl/y by 2050 (ESI†, Figure S3). Correspondingly, total crude input is expected to decrease from 16.8 million barrels per day (MMbbl/d) in 2019 to 13.6 MMbbl/d in 2035 and 12.2 MMbbl/d in 2050 (ESI†, Figure S4).

Table 1. Transportation Fuel Demand Scenarios Considered in the Study

Year	Fuel Demand Scenarios	Scenario Names	Proportion of EV in U.S. Vehicle Fleet, %	Estimated U.S. Liquid Transportation Fuel Demand, Gbbl/year	Estimated Total U.S. Refinery Production, Gbbl/year	Data Source
2019	Baseline Petroleum Fuel Demand	BL	0.503	5.54	7.20	EIA[1]
2035	High Petroleum Fuel Demand	HD35	10.9	4.71	6.80	EFS[4]
2050	High Petroleum Fuel Demand	HD50	13.6	4.58	6.87	EFS[4]
2035	Medium Petroleum Fuel Demand	MD35	42.3	3.74	5.76	EFS[4]
2050	Medium Petroleum Fuel Demand	MD50	64.4	3.04	5.13	EFS[4]
2035	Low Petroleum Fuel Demand	LD35	46.7	3.47	5.32	EFS[4]
2050	Low Petroleum Fuel Demand	LD50	82.3	2.10	3.69	EFS[4]

We then use PRELIM to estimate the GHG emissions for each combination of transportation fuel demand and crude oil input. The exact date that a level of demand is realized in these scenarios is not the focus of this study. Instead, Figure 1 presents the relationship between fuel demand, GHG emissions based on crude input consumed, and the impact of possible carbon capture deployment options for the refining sector. For the LD scenario, as the transportation fuel demand decreases from 5.54 Gbbl/y to 3.47 Gbbl/y and then further declines to 2.10 Gbbl/y, U.S. refinery GHG emissions are projected to decrease by 24.5%, from 212 to 158 million metric tons of CO_2 equivalent per year ($MtCO_2eq/y$) between 2019 and 2035, followed by a further decline to 111 $MtCO_2eq/y$ by 2050. Implementing CCS could further decrease GHG emissions from 111 $MtCO_2/y$ to 47.6 $MtCO_2eq/y$ (i.e., a reduction of 57.3% or 63.9 $MtCO_2eq/y$), assuming maximum adoption of CCS. It should be noted that maximum carbon capture refers to the case where post-combustion carbon capture is deployed on all process furnaces/boilers as well as the FCC regenerator within the refinery, while minimum carbon capture refers only to deploying post-combustion carbon capture on the FCC regenerator. It is important to note that the absorption unit for steam methane reforming (SMR) is assumed to be placed after the furnace, where natural gas and tail gas from the hydrogen purification unit are mixed and combusted. In HD35 and HD50 scenarios, fuel demand is estimated to decline from 5.54 Gbbl/y to 4.71 Gbbl/y and further decrease to 4.58 Gbbl/y. Despite this downward trend, refinery GHG emissions first decrease by 4.50 $MtCO_2eq/y$ and then increase by 2.64 $MtCO_2eq/y$, driven by a slight rise in refinery production from 6.80 Gbbl/y to 6.87 Gbbl/y (Figure S3, ESI†). This apparent discrepancy is primarily due to differing rates of change in product demand and production across regions between HD35 and HD50 (Table S11, ESI†). Further details are provided in Supplemental Result 1 (ESI†). Moreover, implementing maximum carbon capture could reduce GHG emissions by 120-122 $MtCO_2eq/y$, representing a 56.6%-57.4% reduction compared to the BL scenario. In contrast, in LD35 and LD50 scenarios, maximum carbon capture, combined with reduced production, results in an annual emissions decrease of 145-164 $MtCO_2eq/y$, achieving a 68.4%-77.6% reduction compared to the BL scenario. These results demonstrate that carbon capture can reduce GHG emissions even with lower refinery production. As depicted in Figure S5 (ESI†), the deployment of carbon capture technologies could ensure that the refining sector stays on an emissions

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reduction target trajectory until the mid-2030s, regardless of changes in fuel demand. However, beyond this time period, additional measures would be needed to achieve zero emissions for the refining sector and a net-zero target for the entire supply chain. This is due to the fact even with decreasing demand for liquid transportation fuels and deployment of carbon capture, a remaining 47.6 – 67.0 $MtCO_2eq/y$ of GHG emissions would still need to be addressed. Such additional measures could include transitioning to biomass feedstocks, utilizing low-carbon electricity, adopting green/pink hydrogen.[10,20] Simplifying assumptions such as holding the local production share of fuel consumed in a PADD at historic averages and limiting the variation in future crude quality (using only "high" and "low" bounding cases) limits the resulting variability of the GHG emissions from the U.S. refining sector predicted by the model. Because the model does not endogenously reallocate production across regions, it may underrepresent the full scope of future product mix adjustments. However, these assumptions enable us to isolate and evaluate the dominant driver of emissions change (i.e., declining fuel demand), while maintaining transparency in regional accounting. Similarly, our simplified assumptions on the potential range of crude qualities have a secondary influence on aggregate emissions outcomes: the difference in annual U.S. refining-sector GHG emissions between heavy/sour and light/sweet crude scenarios in 2050 is approximately 6 $MtCO_2eq/y$, corresponding to about 5.4% of total refining-sector emissions (ESI†, Figure S6).

Lastly, even if the refinery emissions were reduced to zero, any emissions from upstream and combustion of liquid fuels (e.g., in internal combustion engines) will result in emissions that also need to be mitigated to achieve "net zero" across this supply chain. Although the LD50 scenario (i.e., 2.10 Gbbl/y) and aggressive deployment of carbon capture can reduce the sectoral emissions by 77.6%, it still results in 47.6 $MtCO_2eq/y$ of emissions from the refining stage, 109 $MtCO_2eq/y$ of emissions from the crude upstream activities (i.e., extraction and transportation) and 827 $MtCO_2eq/y$ of emissions when these fuels are combusted (ESI†, Figure S7). The decrease in GHG emissions in downstream fuel combustion is primarily driven by the reduction in GHG emissions from gasoline combustion. In the BL scenario, gasoline accounted for 56.8% of total fuel combustion GHG emissions, contributing 1,184 $MtCO_2eq/y$ out of a total of 2,087 $MtCO_2eq/y$. In the LD50 scenario, gasoline contributes only 31.3% of total fuel combustion emissions, amounting to 259 $MtCO_2eq/y$ out of a total of 827 $MtCO_2eq/y$ (ESI†, Figure S8). Note that PRELIM does not have an emissions factor inventory for the direct combustion of refinery-derived fuels, nor does it have emissions factor inventory for crude upstream activities. Hence, we adopted those emissions factors for downstream fuel combustion from the EIA[54] and emissions factor for crude upstream activities from Sun et al[20]. Consequently, further exploration of reductions across the supply chain is needed to achieve the societal net-zero targets.

Emissions Reduction Potential and CO_2 Avoidance Cost of Carbon Capture for U.S. Refineries

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Figure 2 shows that the CO_2 avoidance cost associated with CO_2 capture from 8 different individual/grouped (i.e., AT & VDU, CNR, FCC, Coker, hydrotreaters, SMR, steam boiler and other units) process units in U.S. refineries varies by more than an order of magnitude (from \$83.5/t to exceeding \$1360/t CO_2 avoided), under an MD50 scenario when the crude proxy (i.e., a mix of different crudes from different oil fields) with low API gravity and high sulfur content (i.e., heavy/sour crude proxy) is processed. The cost would be different if the crude proxy had high API gravity and low sulfur content (i.e., light/sweet crude proxy), as less energy is generally required for refineries to process such crude compared to a heavy/sour crude proxy. Comparing these costs to current U.S. carbon prices (e.g., \$75.0/t CO_2 in 2025 from California's Low Carbon Fuel Standard), it is unlikely to see carbon capture deployed on any of these units as the current price is not only insufficient but also highly volatile, reducing the incentive for long-term investment. As shown in Figure 2 A) and B), if carbon prices were to increase to \$100/t and \$150/t, 11.6 $MtCO_2eq$/year (12.3%) and 53.0 $MtCO_2eq$/year (56.4%) of the total potential avoided emissions (94.0 $MtCO_2eq$/year), respectively, could be achieved. A carbon price of \$400/t is required to unlock 93.8 $MtCO_2eq$/y of emissions reductions, representing 99.8% of the total mitigation potential. For comparison, Canada's federal carbon price is scheduled to reach CAD 170/t CO_2 by 2030 (~122 \$/t CO_2). [55] At this level, the model indicates that FCC units at medium and deep conversion refineries and SMR units at deep conversion refineries in PADD 3 would deploy CCS, achieving 16.6 $MtCO_2eq$/y (17.6%) of emissions reductions. These are associated with very high-cost carbon capture deployment cases within hydroskimming refineries, such as steam boilers.

From a process unit perspective, Figure 2 A) suggests that FCC units should be prioritized for deploying carbon capture in U.S. refineries due to the higher emissions reduction potential and lower avoidance cost. Specifically, applying carbon capture to FCC units can achieve a reduction potential of 18.5 $MtCO_2$/y,

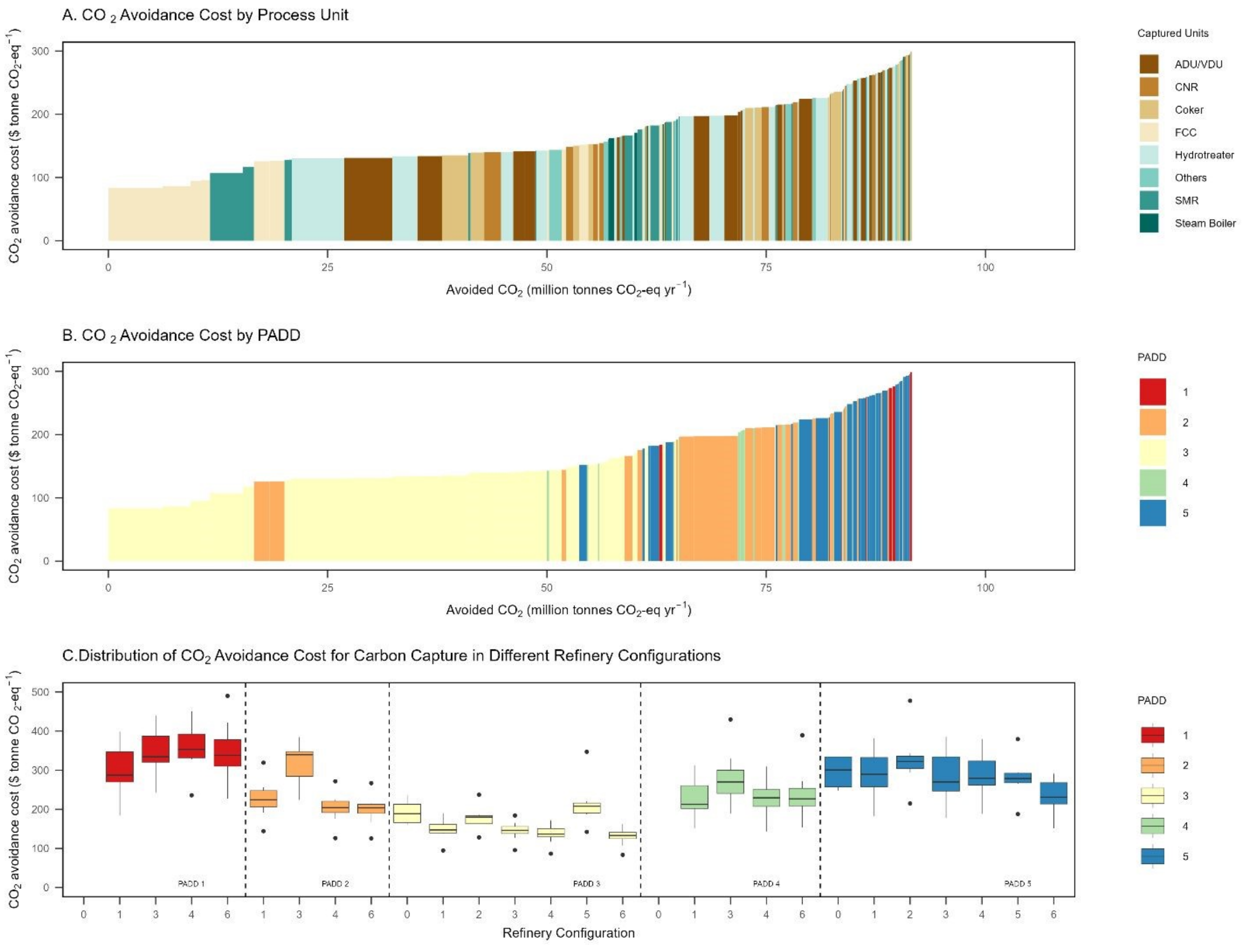

Figure 2. A) CO_2 Avoidance Cost Curve of Carbon Capture and Storage in Different Process Units in U.S. Refineries under MD50 Scenario with Heavy/Sour Crude Proxies Input. B) CO_2 Avoidance Cost Curve of Carbon Capture in Different PADD regions in U.S. Refineries under MD50 Scenario with Heavy/Sour Crude Proxies Input. C) Distribution of CO_2 Avoidance Cost of Carbon Capture in Different Refinery Configurations Grouped by PADD Regions. Each rectangle in figure A) and B) represents an individual/grouped process unit in different refinery configurations in different PADD regions. X-axis for figure A) and B) are the cumulative annual avoided CO_2 by mass ($MtCO_2$/y). X-axis for figure C) represents different refinery configurations from 0 to 6 based on PRELIM classification (ESI†, Table S1). Y-axis upper limits are set to be 250, 250 and 400 \$/tCO_2 respectively. The detailed CO_2 avoidance cost under different fuel demand and crude quality scenarios is presented in Dataset S1 in ESI†. ADU/VDU – Atmospheric Distillation Unit & Vacuum Distillation Unit. CNR – Catalytic Naphtha Reformer. FCC/RFCC – Fluid Catalytic Cracker & Residue Fluid Catalytic Cracker. Hydrotreaters – Naphtha Hydrotreater (NHT), Kerosene Hydrotreater (KHT), Diesel Hydrotreater (DHT), FCC Post Hydrotreater (FCC PHT), Coker Naphtha Hydrotreater (Coker NHT) & Residue Hydrotreater (RHT). SMR – Steam Methane Reforming.

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accounting for 8.73% of the total U.S. refining emissions, while also attaining an avoidance cost ranging from \$83.5/t to \$242/t under the MD50 scenario. FCC units facilitate the conversion of heavy components of crude oil into valuable lighter products such as transportation fuels.[56] They are identified as one of the most emissions-intensive units, with an estimated volume-weighted average emissions intensity of 31.6kg CO_2eq/bbl of crude fraction processed in the U.S., as shown in Table S12, ESI†. Such a high emissions intensity results from the combustion of deposited coke on catalysts, which generates the necessary heat to operate the unit at high temperatures (480 to 540 °C) as well as substantial electricity consumption.[56] Plus, refineries equipped with FCCs are the dominant GHG emissions contributors (i.e., 84.6% to 93.4%) in the U.S. from 2019 to 2050 (ESI†, Table S13). In addition, the cost-effectiveness of carbon capture on FCC units arises from their higher CO_2 concentration (i.e., 16.9 vol%) in the exhaust flue gas, compared to flue gas from other process units (i.e., 6 – 12.5 vol%) (ESI†, Table S14). This higher concentration allows for the use of a smaller absorber and thus lower energy use, leading to reductions in both capital and operation & maintenance costs.

Notably, refiners could achieve lower CO_2 avoidance costs by pooling flue gases from multiple process units into a single absorber and regenerator. This approach would mix gas streams from multiple process units of varying concentrations (from less than 13 to 17 vol%), increasing the total amount of CO_2 captured. For instance, in a deep conversion refinery in PADD 3, the capture of CO_2 from both FCC and SMR units yields an avoidance cost of \$91.2/t, with a total avoided CO_2 of 10.1 $MtCO_2$/y. Although this cost is higher than that from capturing solely from FCC units (\$83.5/t with 6.22 $MtCO_2$/y avoided), it remains lower than the cost of capturing exclusively from SMR units, which stands at \$107/t with 3.79 $MtCO_2$/y avoided, while achieving a higher total avoided CO_2 compared to capturing from either unit alone, as detailed in Dataset S2, ESI†.

We estimate avoidance costs from SMR units across the U.S. span a wide range depending on the stream: \$82.8–811/t for PSA inlet, \$84.6–894/t for PSA outlet, and \$107–853/t for furnace outlet. This is generally higher than costs reported previously (19.8 to 153\$/t CO_2 avoided[21,57–65]) for two reasons: 1) we consider the transportation & storage cost for CCS as well as the leakage rate of CO_2 storage (this adds ~11\$/t in avoidance costs, see Method); 2) we consider the cost for the interconnection pipelines for carbon capture, which are often excluded from literature estimates and could take up to 52% of total capital expenditure (CapEx) under high CO_2 volume flows. It is also notable that our SMR avoidance cost estimates vary widely across refinery configurations due to differences in hydrogen demand and CO_2 flow rates. In refineries with low H_2 use, such as hydroskimming or FCC-only configurations, poor economies of scale result in very high capture costs (e.g., up to \$2,800/t), while hydrogen-intensive sites like deep conversion refineries with hydrocrackers consistently show SMR as one of the lowest-cost options. A detailed explanation of these costing results is presented in Supplemental Result 2 (ESI†). This variation is not typically considered in previous estimates where the ideal applications of carbon capture are typically modelled (e.g., capturing CO_2 from streams with higher concentration or partial pressure).

Figure 2 B) also suggests substantial regional and configuration-level heterogeneity in CCS avoidance costs. Specifically, deploying carbon capture in deep conversion refineries (configuration 6) in PADD 3 could achieve a lower avoidance cost relative to others (i.e., an average of \$129/t for configuration 6 vs. \$169/t for other configurations and \$327/t for other regions) due in large part due to the large volume of CO_2 avoided reducing the marginal cost of capital expenditure. These refineries (in PADD 3 alone) are estimated to account for 28.0% of the total crude processed in the U.S., leading to 30.1% of total GHG emissions under an MD50 scenario. This makes them the largest contributor to GHG emissions compared to refineries in other configurations. PADD 3 is also estimated to have the lowest construction cost compared to other regions, owing to the lower construction cost location factor (ESI†, Table S15) in the U.S. Gulf Coast region. Note that the cost of CO_2 transportation via pipeline and storage has also been considered in Figure 2. For the scenario involving 100 $MtCO_2$/y, the estimated unit costs are \$4.37/t for storage and \$6.31/t for transportation as mentioned in Methods. Past studies show the cost for CO2 transportation and storage could vary in different regions, ranging from 10 – 22 \$/t.[66] A sensitivity analysis was conducted to evaluate the impact of this variability on the overall avoidance cost (ESI†, Supplementary Result 3). The results indicate that CO_2 transportation costs via pipeline are not a primary driver of avoidance cost relative to capture costs, although they remain non-negligible. Accordingly, while capture costs dominate, refineries should still account for location-specific transport and storage costs, alongside carbon capture and carbon pricing, when making investment decisions.

Likely Reactions of Different Refinery Archetypes under Uncertain Future Market and Carbon Pricing Conditions

In the face of uncertain future regional transportation fuel markets and carbon pricing conditions, refineries will react in different ways (e.g., continue business as usual operations, shut down, invest in GHGs mitigation technologies). Figure 3 A) illustrates that under various uncertain conditions - including fluctuating prices of crude oil, refinery products, utilities, and carbon dioxide, as well as changing fuel demand, medium and deep conversion refineries are unlikely to shut down (see

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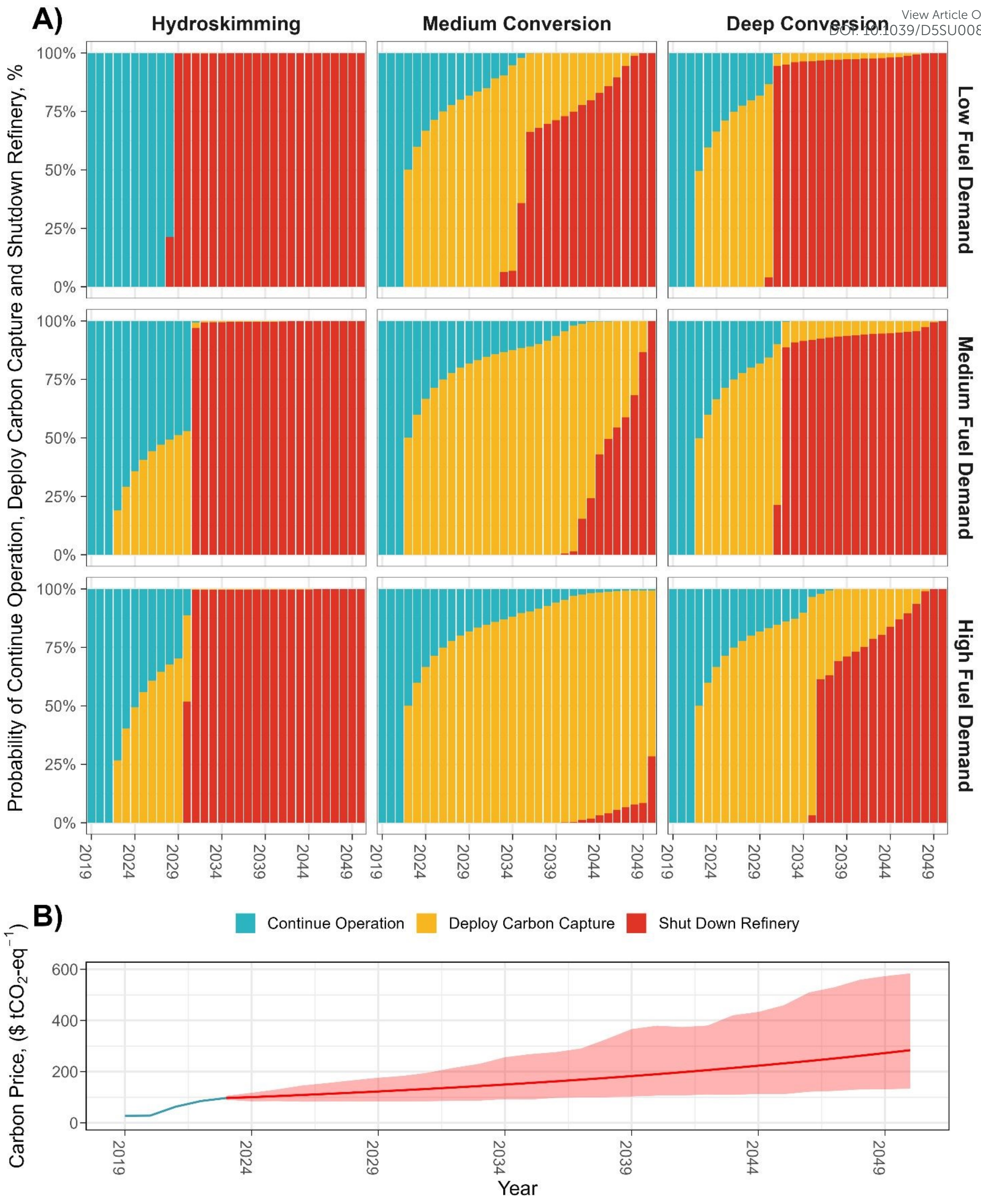

Figure 3. A) Likelihood of Three Choices Using Real Options Analysis for Three Refinery Types under Three Transportation Fuel Demand Scenarios. B) Simulated Carbon Price Trajectories Assumed to Follow Stochastic Process. The Low/Medium/High fuel demand scenarios refer to the fuel demand transition from the BL scenario to LD35/50, MD35/50 and HD35/50 scenarios, respectively. Carbon prices are assumed to follow a stochastic process (GBM), and could range from \$27.8/t to \$584/t. A single binomial lattice is generated based on a specific carbon price trajectory. A Monte Carlo simulation is then employed, sampling various carbon price trajectories that adhere to the GBM process to create a set of binomial lattices (i.e., 10,000 runs). The likelihood of each response at a specific time is calculated by dividing the number of nodes executing the response by the total number of nodes at that time (see Supplementary Method 3, ESI †). Hydroskimming refers to Hydroskimming Configuration (0). Medium Conversion refers to Medium Conversion: FCC & GO-HC (3). Deep Conversion refers to Deep Conversion: FCC & GO-HC (6).

Supplementary Method 3, ESI†). For example, the likelihood of

shutdown rises to 87.4% during the same period. It is important

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to note that this analysis only considered three possible actions. Other technologies and strategies could become profitable options in place of shutting the refinery down.

Additionally, a sensitivity analysis is conducted to assess how the likelihood of the three actions for a medium conversion refinery varied under a medium fuel demand scenario (ESI†, Figure S9). This sensitivity analysis varied five key variables: risk-free interest rate, crack spread (i.e., the margin a refiner realizes while procuring crude oil and simultaneously selling the products),[67] carbon prices, CCS utility costs, and CCS capital costs, each considered under High, Reference, and Low scenarios. The risk-free interest rate ranges from 1% to 7%, based on historical U.S. Treasury bond rates. Crack spread scenarios are derived from the AEO's low, reference, and high oil price cases to reflect fuel price dynamics.[52] Carbon prices are varied by ±50% from the baseline trajectory used in the main RO analysis, while CCS utility and capital costs are also adjusted by ±50% to represent potential technological advances or setbacks. The specific variations applied to each variable are summarized in Table S16 (ESI†).

Among these factors, crack spread has the largest impact on the likelihood of shutting down a medium conversion refinery as shown in Figure S9 (ESI†). Under the Low crack spread scenario, the medium conversion refinery archetype is likely to consider closure as early as the early 2030s, with the probability of shutting down rising sharply from 11.3% in 2028 to 96.2% by 2030. In contrast, under the High crack spread scenario, the refinery is more likely to consider CCS deployment instead, as the likelihood of shutdown remains negligible - 0.03% by 2045 - before rising modestly to 19.8% by 2050. These results suggest that successfully reducing transportation fuel demand (e.g., through widespread EV adoption) could shift market conditions toward a lower crack spread, thereby increasing the likelihood of refinery closure. Conversely, a high crack spread could prolong the operation of medium conversion refineries and reduce the incentive to deploy CCS. While our model does not directly capture the complexities of market dynamics (i.e., correlating the EV demand to crude and fuel prices), this relatively simple model still identifies a potential risk of unintended outcomes - such as delayed decarbonization - when fuel demand reduction is paired with complementary policy measures (e.g., crude supply interventions, refining subsidies).

Carbon pricing is another key driver influencing a refiner's decisions. A high carbon price encourages earlier CCS deployment in the medium conversion refinery archetype, with a 33.3% probability of adoption emerging in the early 2020s, compared to 50.0% under the reference case. However, if CCS investment is delayed beyond the mid-2040s, the economic pressure from high carbon prices increases the risk of shutdown, with the probability exceeding 50% during that period. Conversely, a low carbon price reduces the incentive to deploy CCS - dropping the probability to just 0.305% by 2030 - and prolongs refinery operations, keeping shutdown likelihood as low as 0.140% by the mid-2040s. Still, even with low carbon prices, refinery shutdowns may occur after 2050, driven by deteriorating market conditions such as declining fuel demand and narrower crack spreads. The results for the two additional carbon price trajectory scenarios are presented in Supplementary Result 4.

Discussion

In this work, we evaluate how transitions in transportation fuel demand and the quality of crude mix consumed in refineries in the U.S. can impact refinery operations and sectoral GHG emissions. We estimate that ~212 $MtCO_2eq$/y of GHG emissions (i.e., including natural gas extraction and power generation emissions generated by the utilities consumed by refineries) can be attributed to the U.S. refining sector in 2019. If carbon capture is employed extensively, over 126 $MtCO_2eq$/y (i.e., 59.1% of reduction) of GHG emissions can be mitigated. As a comparison, Sun et al.[20] reported emissions of 196 $MtCO_2eq$/y from U.S. refineries in 2019 and argued that CCS could reduce 67.4%-90% of on-site CO_2 emissions. Yao et al.[18] compared two carbon capture strategies in the U.S. refining sector: 1) post-combustion with amine scrubbing and 2) pre-combustion coupled with oxy-fuel combustion capture. They reported a total reduction potential of 100 $MtCO_2eq$/y in 2014, with pre-combustion coupled with oxy-fuel combustion being more cost-effective compared to post-combustion carbon capture. Our findings on total refining sector GHG emissions and reductions achievable through CCS are consistent with these estimates, but also reveal the strong interaction between transportation fuel demand and refining sector GHG emissions. Specifically, demand contraction alone can reduce emissions by 48% (to 111 $MtCO_2eq$/yr), while full deployment of carbon capture can further decrease emissions to 47.6 $MtCO_2eq$/yr, equivalent to a 57.3% reduction. It should also be noted that the premises of the decreasing petroleum fuel is the increasing electrification of the vehicle fleet. However, the future EV demand is highly uncertain due to policy uncertainty [68] and critical mineral supply chain constraints. [69]

On the other hand, we conclude that deploying carbon capture in FCC units could be economically attractive to refiners as it could potentially avoiding GHG emissions by 18.5 MtCO2eq/y, accounting for 8.73% of total U.S. refineries' GHG emissions, while also attaining a cheaper avoidance cost ranging from \$83.5/t to \$242/t under an MD50 scenario compared to other process units. Previous studies by Van Straelen et al.[14] and Gale et al. [21] examined the complexity of deploying carbon capture in refineries as carbon sources scattered throughout the refinery and the estimated CO_2 avoidance cost vary widely. They concluded that refinery process units with medium to high CO_2 concentrations had the most favorable avoidance cost, while capturing from small emitters with low concentrations was less economically effective, which our study agree. We also conclude that capturing CO_2 from pooled flue gases with different CO_2 concentrations from multiple process units could be attractive to refiners. We find that capturing CO_2 from all furnaces/boilers along with the FCC regenerator is achievable at \$125/t, which is close to the estimated cost by Gale et al.[21] at around \$160-210/tCO_2. However, we find that our estimated avoidance costs for SMR (i.e., \$107–853/t) are higher and span a wider range than those reported in previous studies (i.e.,

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19.8–153\$/t).[21,57–65] The higher costs primarily reflect differences in assumptions regarding cost for CO_2 transportation and storage, interconnection infrastructure, and capture location, while the wider range arises from variation in refinery configurations and regions—an aspect not examined in earlier analyses.

We are also the first, to our knowledge, to employ RO analysis to examine the strategic decisions of continuing operation, deploying carbon capture and shutting down that could be made by U.S. refineries. RO analysis extends financial option pricing methods to evaluate investment decisions under uncertainty, enabling the valuation of flexibility and strategic choices in managing real assets[50,70,71]. Multiple studies have also been conducted using RO in the past to investigate the condition and timing or optimal low-carbon technology investment in the energy sector.[72–75] Reinelt et al. [72] developed a stochastic dynamic programming model to evaluate strategies for aging pulverized coal plants under uncertain carbon regulations, including continuing operations or building new facilities with advanced technologies (e.g., natural gas combined cycle plant, or integrated gasification combined cycle plant), with or without CCS. Their results showed that a preferred market (i.e., low natural gas prices) with higher carbon taxes favors investing in carbon mitigating technologies. McKeller et al.[73] used a quadrinomial tree model and stochastic dynamic programming to evaluate nine alternative uses for Alberta oil sands coke, including hydrogen production and electricity generation, with or without CCS. Their findings showed that higher carbon taxes shift preference from sending the coke overseas for electricity generation without mitigating technologies to having the coke consumed by the nearest market with the application of CCS, which offers superior financial and emissions performance under high carbon pricing scenarios. Similarly, our study concludes that, under the modeled crack spread and carbon price scenarios, favorable market conditions (i.e., high crack spread), with higher carbon costs, would encourage the deployment of CCS. However, we also find that certain refinery configurations, such as hydroskimming, are highly sensitive to market fluctuations and carbon pricing policies, making them more exposed to the risk of shutdown by the early 2030s, while medium- and deep-conversion refineries are more likely to consider deploying carbon capture beginning in the early 2020s and potentially continuing through the 2040s under the assumed transportation fuel demand scenarios and modeled carbon price trajectories. Notably, the modeled results indicate that the window of opportunity for taking action is relatively narrow: the probability of refinery shutdown begins to increase markedly by the 2040s under these assumptions.

Future Work Opportunities

This study relies on a number of simplifying assumptions that facilitate long-term scenario analysis but limit the scope of the results and point to several avenues for future research. Namely, the analysis is intended to examine refinery-level emissions mitigation potential and strategic investment responses under stylized demand, technology, and policy scenarios, rather than to predict endogenous market outcomes such as inter-regional trade reallocation, equilibrium fuel prices, or strategic interactions among refineries. The simplified assumption of fixed historical local production shares could be relaxed in future work by integrating an explicit multi-region partial equilibrium framework that endogenizes trade and product allocation decisions, allowing for exploration of variability in product slates and associated GHG emissions under alternative market and policy conditions. It should be noted, however, that this will come at the expense of the detailed technology representation used in the current work. The simplified representation of future crude qualities could be extended by incorporating supply-driven constraints and alternative crude-availability scenarios that reflect potential shifts in aggregate API gravity and sulfur content due to resource depletion, geopolitical disruptions, or changes in global production portfolios, thereby allowing the framework to explore how different crude-quality pathways influence refining-sector emissions under alternative market and policy conditions. Region-specific CCS network modeling could be incorporated to represent spatial variation in transport distances, storage availability, and infrastructure build-out, thereby enabling the framework to examine how regional differences in CO_2 transport and storage systems influence deployment feasibility and total mitigation costs. Price simulation could be extended to incorporate multivariate stochastic processes or explicitly modeled correlations among carbon prices, fuel prices, and other economic variables, enabling the framework to examine how joint uncertainty shapes investment timing and risk exposure. Finally, the analysis is based on stylized refinery archetypes and scenario assumptions, and results should be interpreted as conditional insights rather than deterministic or causal forecasts. Future work could employ agent-based modeling to capture interactions among refineries and assess how facility-level decisions, such as shutdowns or CCS investments, propagate through the sector.

Conclusions

Policies and market trends that reduce transportation fuel demand, such as the electrification of vehicle fleets, have the potential to lower GHG emissions in the refining sector by 45% from 2019 to 2050. However, the anticipated reduction in fuel demand resulting from high electric vehicle deployment will be insufficient to meet the emissions reduction target (e.g., net-zero by 2050). Therefore, if this target is to be met, additional efforts are required, including the deployment of CCS. CCS could potentially reduce remaining refining GHG emissions by 77.6% under a low fuel demand scenario in 2050 (i.e., LD50) compared to 2019 levels. Furthermore, even under a high fuel demand scenario in 2050 (i.e., HD50), carbon capture could reduce 58.0% in refining emissions, resulting in sectoral GHG emissions of 122 $MtCO_2/y$. This reduction can help the refining sector in the mid-transition towards deep decarbonization targets but could also signal to a refinery that they hesitate to invest more

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or shut down once they invest in carbon capture. However, the analysis suggests that mitigation strategy such as CCS alone is not enough to fully decarbonize the supply chain under the modeled transportation fuel demand scenarios. Further measures, such as carbon dioxide removal (CDR), therefore will be required.

The competitiveness of deploying carbon capture on certain process units was evaluated depending on their emissions reduction potential and CO_2 avoidance costs. Flue gas streams with higher CO_2 concentration and volume (e.g., FCC, CNR, AT, SMR) are likely to be prioritized for carbon capture. Deploying carbon capture in some refinery configurations in certain regions is cheaper than others (e.g., FCC, SMR from deep conversion refinery in PADD 3) and thus is also likely to be considered for early deployment.

In the face of uncertain future transportation fuel demand and carbon pricing stringency, refineries must navigate a complex decision-making landscape. Within the modeled refinery archetypes, hydroskimming refinery, which are particularly sensitive to carbon pricing and declining fuel demand, are estimated – under the modeled carbon price trajectories – to face a 99% likelihood of shutdown by the early 2030s, as these factors critically undermine their financial viability. Conversely, the medium- and deep-conversion refinery archetypes exhibit greater resilience, with no immediate signals to shut down, and the modeled results suggest that they may consider deploying carbon capture technologies as early as 3 years after the start of the RO simulation to enhance their operational sustainability. The RO analysis suggests a narrow but critical window under the modeled assumptions, during which refineries - particularly medium conversion archetypes - can take strategic action to maintain economic viability during a low-carbon transition. Sensitivity analysis shows that both crack spread and carbon pricing impact the likelihood and timing of key decisions, such as deploying CCS or shutting down operations. The key insight is that refinery decisions are highly sensitive to both the magnitude and the timing of these signals; if mistimed, refineries may make decisions that are misaligned with long-term policy goals.

In general, we conceptualize CCS in refineries as serving both a transitional mitigation function and, under certain conditions, a means of extending operational lifetimes. On the one hand, CCS can reduce refinery-level emissions and, under declining fuel demand scenarios, help maintain emissions trajectories consistent with near-term decarbonization pathways by mitigating a large share of operational emissions and enabling refineries to continue providing essential fuel services while replacement low-carbon systems are deployed. On the other hand, although CCS deployment may enhance near-term economic viability by lowering carbon cost exposure and stabilizing margins under assumed carbon price trajectories, these reductions are largely confined to captured process emissions and do not eliminate residual refinery emissions or upstream and downstream supply chain emissions. As such, CCS alone does not ensure long-term competitiveness in a deeply decarbonized system. The real-options analysis indicates whether CCS functions primarily as a bridge strategy or as a mechanism that prolongs carbon-intensive operations depends on the magnitude and timing of market and policy signals. Declining demand may also push some refineries toward minimum viable operating scales, increasing the risk of abrupt shutdowns that could disrupt supply and create safety or system-level challenges. [76] Measures that reduce investment risk can shift the timing and scale of CCS deployment. These include investment-based instruments such as the U.S. 45Q tax credit (i.e., Credit for Carbon Oxide Sequestration) under the Inflation Reduction Act, which provides incentives for entities that capture CO_2, [77] as well as price-based approaches such as carbon price corridors (or “price collars”), which establish upper and lower bounds on carbon prices (e.g., mechanisms under the German ETS). [78] In a North American context, policies that strengthen effective carbon price floors - such as proposed increases to the Alberta Technology Innovation and Emissions Reduction (TIER) benchmark price - may serve a similar function. [79] In addition, long-term contracting mechanisms, including carbon contracts for difference (CCfDs) with governments and project developers, can also mitigate investment uncertainty by stabilizing expected carbon revenues over project lifetimes. [80] However, such interventions must be designed to balance the objective of a secure supply of refinery products that are expected to change in unprecedented ways over the coming two decades and long-term decarbonization goals. In this context, enabling near-term abatement through CCS should be balanced with coordinated demand-side transitions, upstream decarbonization, and complementary mitigation pathways, so that the pace of declining transportation fuel demand is aligned with supply-side adjustment and transitional emissions reductions at the refinery level do not delay system-wide alignment with long-term climate goals.

Author contributions

F.L.: conceptualization, data curation, formal analysis, investigation, methodology, software, validation, visualization, writing – original draft. L.J.: resources, software, writing – review & editing. S.M: validation, writing – review & editing. S.H: writing – review & editing. J. B: conceptualization, funding acquisition, project administration, software, resources, supervision and writing – review & editing.

Conflicts of interest

There are no conflicts to declare.

Data availability

The PRELIM model supporting this study is an unpublished version and will be made accessible upon request. The real option model, code and subset data (including the supplementary data sets and figure plotting dataset) supporting this study is included in public repository: https://doi.org/10.5281/zenodo.16052925. The Monte Carlo simulation results for real option can be found in https://doi.org/10.5281/zenodo.15938756.

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References

1 Total Energy Monthly Data - U.S. Energy Information Administration (EIA), https://www.eia.gov/totalenergy/data/monthly/index.php, (accessed 27 April 2023).
2 C. Watson, *2011-2021 Greenhouse Gas Reporting Program Industrial Profile: Petroleum Refineries Sector*, EPA.
3 V. Masson-Delmotte, H.-O. Pörtner, J. Skea, P. Zhai, D. Roberts, P. R. Shukla, A. Pirani, R. Pidcock, Y. Chen, E. Lonnoy, W. Moufouma-Okia, C. Péan, S. Connors, J. B. R. Matthews, X. Zhou, M. I. Gomis, T. Maycock, M. Tignor and T. Waterfield, *An IPCC Special Report on the impacts of global warming of 1.5°C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change, sustainable development, and efforts to eradicate poverty*, .
4 T. T. Mai, P. Jadun, J. S. Logan, C. A. McMillan, M. Muratori, D. C. Steinberg, L. J. Vimmerstedt, B. Haley, R. Jones and B. Nelson, *Electrification Futures Study: Scenarios of Electric Technology Adoption and Power Consumption for the United States*, 2018.
5 U.S. Refinery Crude Oil Input Qualities, https://www.eia.gov/dnav/pet/pet_pnp_crq_dcu_nus_m.htm, (accessed 27 April 2023).
6 D. of S. U.S., *The United States' Nationally Determined Contribution: Reducing Greenhouse Gases in the United States: A 2030 Emissions Target*, 2021.
7 J. Bistline, G. Blanford, M. Brown, D. Burtraw, M. Domeshek, J. Farbes, A. Fawcett, A. Hamilton, J. Jenkins, R. Jones, B. King, H. Kolus, J. Larsen, A. Levin, M. Mahajan, C. Marcy, E. Mayfield, J. McFarland, H. McJeon, R. Orvis, N. Patankar, K. Rennert, C. Roney, N. Roy, G. Schivley, D. Steinberg, N. Victor, S. Wenzel, J. Weyant, R. Wiser, M. Yuan and A. Zhao, *Science*, 2023, **380**, 1324–1327.
8 Congress Climate History, https://www.c2es.org/content/congress-climate-history/, (accessed 25 February 2025).
9 T. Hale, T. Wetzer, S. K. Abebe, M. Allen, A. Amel-Zadeh, J. Armour, K. Axelsson, B. Caldecott, L. Dias, S. Fankhauser, B. Franta, C. Hepburn, K. Mbeva, L. Rajamani, S. Smith and R. Stuart-Smith, *Nat. Clim. Chang.*, 2024, **14**, 306–308.
10 H. Kim, Ph.D. Thesis, University of Calgary, 2023.
11 W. Li, C.-W. Hui and A. Li, *Computers & Chemical Engineering*, 2005, **29**, 2010–2028.
12 J. Fallurin, T. J. Conway and T. J. Kirk, *Oil refining emissions cut points: Downstream decarbonization in the decisive decade*, RMI, 2022.
13 S. Jiang, *Journal of Applied Statistics*, 2012, **39**, 1505–1530.
14 J. van Straelen, F. Geuzebroek, N. Goodchild, G. Protopapas and L. Mahony, *International Journal of Greenhouse Gas Control*, 2010, **4**, 316–320.
15 K. Heal and T. Kemp, *Energy Procedia*, 2013, **37**, 7046–7055.
16 D. Johansson, P.-Å. Franck and T. Berntsson, *Energy Conversion and Management*, 2013, **66**, 127–142.
17 K. Motazedi, J. P. Abella and J. A. Bergerson, *Environ. Sci. Technol.*, 2017, **51**, 1918–1928.
18 Y. Yao, J. Marano, W. R. Morrow and E. Masanet, *International Journal of Greenhouse Gas Control*, 2018, **74**, 87–98.
19 H. Pilorgé, N. McQueen, D. Maynard, P. Psarras, J. He, T. Rufael and J. Wilcox, *Environ. Sci. Technol.*, 2020, **54**, 7524–7532.
20 P. Sun, V. Cappello, A. Elgowainy, P. Vyawahare, O. Ma, K. Podkaminer, N. Rustagi, M. Koleva and M. Melaina, *Environ. Sci. Technol.*, 2023, acs.est.2c07440.
21 J. Gale, *Understanding the cost of retrofitting CO2 capture to an integrated oil refinery*, International Energy Agency, 2017.
22 S. Roussanaly, N. Berghout, T. Fout, M. Garcia, S. Gardarsdottir, S. M. Nazir, A. Ramirez and E. S. Rubin, *International Journal of Greenhouse Gas Control*, 2021, **106**, 103263.
23 S. Fuss, D. J. A. Johansson, J. Szolgayova and M. Obersteiner, *Energy Policy*, 2009, **37**, 733–743.
24 B. Young, M. Krynock, D. Carlson, T. R. Hawkins, J. Marriott, B. Morelli, M. Jamieson, G. Cooney and T. J. Skone, *International Journal of Greenhouse Gas Control*, 2019, **91**, 102821.

View Article Online
DOI: 10.1039/D5SU00853K

25 F. Güleç, W. Meredith and C. E. Snape, *Front. Energy Res.*, 2020, **8**, 62.
26 H. Li, M. Ditaranto and D. Berstad, *Energy*, 2011, **36**, 1124–1133.
27 D. G. Chapel and C. L. Mariz, Saskatchewan, Canada, 1999.
28 T. Mimura, H. Simayoshi, T. Suda, M. Iijima and S. Mituoka, *Energy Conversion and Management*, 1997, **38**, S57–S62.
29 O. Bolland and H. Undrum, *Advances in Environmental Research*, 2003, **7**, 901–911.
30 R. Digne, F. Feugnet and A. Gomez, *Oil Gas Sci. Technol. – Rev. IFP Energies nouvelles*, 2014, **69**, 1081–1089.
31 L. F. de Mello, R. D. M. Pimenta, G. T. Moure, O. R. C. Pravia, L. Gearhart, P. B. Milios and T. Melien, *Energy Procedia*, 2009, **1**, 117–124.
32 W. Chung and J. H. Lee, *Ind. Eng. Chem. Res.*, 2020, **59**, 18951–18964.
33 4-Week Avg U.S. Product Supplied of Petroleum Products (Thousand Barrels per Day), https://www.eia.gov/dnav/pet/hist/LeafHandler.ashx?n=PET&s=WRPUPUS2&f=4, (accessed 6 May 2024).
34 U.S. Refinery and Blender Net Production, https://www.eia.gov/dnav/pet/pet_pnp_refp_dc_nus_mbbl_m.htm, (accessed 27 April 2023).
35 East Coast (PADD 1) Net Receipts of Crude Oil and Petroleum Products by Pipeline, Tanker, Barge and Rail, https://www.eia.gov/dnav/pet/pet_move_netr_d_r10-z0p_VNR_mbbl_m.htm, (accessed 27 April 2023).
36 East Coast (PADD 1) Imports of Crude Oil and Petroleum Products for Processing, https://www.eia.gov/dnav/pet/pet_move_imp2_dc_R10-Z00_mbbl_m.htm, (accessed 27 April 2023).
37 East Coast (PADD 1) Total Crude Oil and Products Exports, https://www.eia.gov/dnav/pet/pet_move_expcp_a2_r10_ep00_eex_mbbl_m.htm, (accessed 27 April 2023).
38 U.S. Refinery Stocks, https://www.eia.gov/dnav/pet/pet_stoc_ref_dc_nus_mbbl_m.htm, (accessed 27 April 2023).
39 Company Level Imports, https://www.eia.gov/petroleum/imports/companylevel/, (accessed 27 April 2023).
40 G. Cooney, M. Jamieson, J. Marriott, J. Bergerson, A. Brandt and T. J. Skone, *Environ. Sci. Technol.*, 2017, **51**, 977–987.
41 W. L. Nelson, *Guide to refinery operating cost (process costimating)*, 1976.
42 W. L. Nelson, *How the Nelson refinery constraction cost indexes evolved*, 1976.
43 W. L. Nelson, *Here's how operating cost indexes are computed*, 1977.
44 U.S. Refinery Yield, https://www.eia.gov/dnav/pet/pet_pnp_pct_dc_nus_pct_m.htm, (accessed 27 April 2023).
45 2021 Worldwide Refining Capacity Summary, https://www.ogj.com/ogj-survey-downloads/worldwide-refining/document/14233364/2021-worldwide-refining-capacity-summary, (accessed 27 April 2023).
46 R. S. Middleton, S. P. Yaw, B. A. Hoover and K. M. Ellett, *Environmental Modelling & Software*, 2020, **124**, 104560.
47 V. E. Onyebuchi, A. Kolios, D. P. Hanak, C. Biliyok and V. Manovic, *Renewable and Sustainable Energy Reviews*, 2018, **81**, 2563–2583.
48 M. D. Jensen, P. Pei, A. C. Snyder, L. V. Heebink, L. S. Botnen, C. D. Gorecki, E. N. Steadman and J. A. Harju, *Energy Fuels*, 2013, **27**, 4175–4182.
49 L. Trigeorgis, *Financial Management*, 1993, **22**, 202.
50 T. E. Copeland and V. Antikarov, *Real Options: A Practitioner's Guide*, Texere, 2001.
51 L. E. Brandão and J. S. Dyer, *Ann Oper Res*, 2005, **135**, 21–39.
52 S. Nalley and A. LaRose, *Energy Information Agency*.
53 Resource Center, https://home.treasury.gov/resource-center/data-chart-center/interest-rates/TextView, (accessed 20 October 2025).
54 U.S. Energy Information Administration - EIA - Independent Statistics and Analysis, https://www.eia.gov/environment/emissions/co2_vol_mass.php, (accessed 4 July 2024).
55 E. and C. C. Canada, The federal carbon pollution pricing benchmark, https://www.canada.ca/en/environment-climate-change/services/climate-change/pricing-pollution-how-it-will-work/carbon-pollution-pricing-federal-benchmark-information.html, (accessed 20 February 2026).
56 J. H. Gary and G. E. Handwerk, *Petroleum refining: technology and economics*, M. Dekker, New York, 4th ed., 2001.
57 D. Mullen, L. Herraiz, J. Gibbins and M. Lucquiaud, *International Journal of Greenhouse Gas Control*, 2023, **126**, 103904.

View Article Online
DOI: 10.1039/D5SU00853K
58 Y. Khojasteh Salkuyeh, B. A. Saville and H. L. MacLean, *International Journal of Hydrogen Energy*, 2017, **42**, 18894–18909.
59 J. C. Meerman, E. S. Hamborg, T. van Keulen, A. Ramírez, W. C. Turkenburg and A. P. C. Faaij, *International Journal of Greenhouse Gas Control*, 2012, **9**, 160–171.
60 I. Lindsay, C. Lowe, S. Reddy, M. Bhakta and S. Balkenende, *Energy Procedia*, 2009, **1**, 4095–4102.
61 M. H. Ali Khan, R. Daiyan, P. Neal, N. Haque, I. MacGill and R. Amal, *International Journal of Hydrogen Energy*, 2021, **46**, 22685–22706.
62 G. Lozza and P. Chiesa, *Journal of Engineering for Gas Turbines and Power*, 2002, **124**, 89–95.
63 F. Pruvost, S. Cloete, C. Arnaiz Del Pozo and A. Zaabout, *Energy Conversion and Management*, 2022, **274**, 116458.
64 D. Bonaquist, *Analysis of CO2 Emissions, Reductions, and Capture for Large-Scale Hydrogen Production Plants*, Praxair, 2010.
65 R. G. Lemus and J. M. Martínez Duart, *International Journal of Hydrogen Energy*, 2010, **35**, 3929–3936.
66 T. Grant, D. Morgan and K. Gerdes, *Carbon dioxide transport and storage costs in NETL studies*, National Energy Technology Laboratory, 2013.
67 M. Exchange, *Crack Spread Handbook*, NewYork: New York Mercantile Exchange, 1989.
68 J. Archsmith, E. Muehlegger and D. S. Rapson, *Environmental and Energy Policy and the Economy*, 2022, **3**, 71–110.
69 L. Woodley, C. Y. See, P. Cook, M. Yeo, D. S. Palmer, L. Huh, S. Wang and A. Nunes, *Nat Commun*, 2024, **15**, 6813.
70 F. Black and M. Scholes, *JOURNAL OF POLITICAL ECONOMY*.
71 J. C. Cox, S. A. Ross and M. Rubinstein, *Journal of Financial Economics*, 1979, **7**, 229–263.
72 P. S. Reinelt and D. W. Keith, *The Energy Journal*, 2007, **28**, 101–128.
73 J. M. McKellar, J. A. Bergerson, J. Kettunen and H. L. MacLean, *Environ. Sci. Technol.*, 2013, **47**, 5979–5987.
74 J.-L. Fan, M. Xu, L. Yang, X. Zhang and F. Li, *Energy Policy*, 2019, **132**, 1229–1240.
75 M. Zhang, L. Liu, Q. Wang and D. Zhou, *Energy Economics*, 2020, **92**, 104954.
76 J. Lappen and E. Grubert, *Science*, 2026, **391**, 449–452.
77 U.S. Congress, 2022.
78 Emissions trading systems, https://www.oecd.org/en/publications/effective-carbon-rates-2025_a5a5d71f-en/full-report/emissions-trading-systems-a-variety-of-designs_b98e7b5c.html, (accessed 17 March 2026).
79 Government of Alberta, *Standard for Developing Benchmarks under the Technology Innovation and Emissions Reduction Regulation*, Alberta Environment and Protected Areas, 2024.
80 International Emissions Trading Association (IETA), *Carbon Contracts for Difference 101*, International Emissions Trading Association, 2023.

View Article Online
DOI: 10.1039/D5SU00853K

Data Sharing Plan

The PRELIM model supporting this study is an unpublished version and will be made accessible upon request. The real option model, code and subset data (including the supplementary data sets and figure plotting dataset) supporting this study is included in public repository: https://doi.org/10.5281/zenodo.16052925. The Monte Carlo simulation results for real option can be found in https://doi.org/10.5281/zenodo.15938756.