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Stochastic modeling of decarbonizing strategy, policy, and market-induced incentives for the US electricity sector

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ABSTRACT

In line with the global pursuit of achieving net-zero carbon emissions, integrating carbon capture and storage (CCS) and renewable energy (RE) technologies is important in power production. This study evaluates the profitability of CCS and RE technologies as alternative ways of achieving climate change goals. While past research focused on costs, technological advancements, and capture methods, there is a need for more studies on assessing the financial feasibility of these climate change solutions under uncertain conditions, alongside specific performance goals and strategies to entice power producers. Using a comprehensive framework featuring deterministic and stochastic modeling approaches, this research explores the impact of policy and market incentives on CCS and RE investments within the U.S. power sector. It analyzes the interactions of variables such as market uncertainties, technical factors, and policy dynamics on the financial viability of adopting CCS and RE for targeted CO_2 reductions. The results reveal that, given the status quo of policies, RE and CCS exhibit annualized net present values of \$4.62 and \$1.76, respectively, for each metric ton (MT) of CO_2. Uncertainties in policy incentives emerge as a primary hindrance to achieving cost-effective carbon reduction mandates using CCS, while changes in the green electricity price premium cause high variability in RE returns. The study proposes a hypothetical market, featuring the sale of CCS-linked net-zero electricity at a distinctive premium price of \$0.03/kWh. The study's findings underscore the importance of both policy and market incentives to enable power producers to deploy carbon management technologies at a large scale.

1. Introduction

With the global goal of meeting net-zero carbon emissions and achieving carbon neutrality, no single technology or reduction strategy will be sufficient to address the overall emission reduction challenge (Pechman et al., 2022). All climate mitigation technologies must be a part of the solution. Due to the increased call for electrification in the transportation sector, as well as increasing residential and industrial energy needs (McCollum et al., 2014; Cho and Strezov, 2020), the electric power sector accounts for close to one-third of the total energy-related CO_2 emissions (United States Energy Information Agency, 2022a, United States Energy Information Agency, 2022b). As a result, deep decarbonization of the electric power sector plays a key role in meeting net-zero emissions goals (Sepulveda et al., 2018; Sanchez and Kammen, 2016; Krey et al., 2014). One way to achieve decarbonization of electricity is by generating cleaner or greener electricity from renewable energy (RE) sources (Patrizio et al., 2018). However, even with a transition to renewable energy sources, the global energy supply is expected to increase by 30% from 2020 to 2050 with supply from oil and natural gas leading the energy market (IEA, 2021).

Larson et al. (2021) and Pechman et al. (2022), among other studies, argued that carbon capture and storage (CCS) technologies are crucial for the United States (US) to meet its net-zero emissions target or nationally determined contribution by 2030 (UNFCCC, 2021). Other studies also examined the role of CCS in decarbonizing power plants (Singh et al., 2022; Sepulveda et al., 2018). Wide-scale deployment of CCS (Koelbl et al., 2014; Muratori et al., 2017) requires a healthy financial net return and economic profitability in addition to issues related to technical feasibility and the availability of supporting infrastructure. Supply-side factors, such as lower capital and operating costs, and policy incentives, determine the degree to which carbon capture and clean production technologies are economically feasible pathways to meeting carbon reduction goals (Pechman et al., 2022). For instance, Singh et al. (2022) examined the cost implications of retrofitting existing fossil plants with a CCS capability and found that even if CCS enables the

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Nomenclature

C_{ST}	The average cost of onshore CO_2 transportation and storage ($/MT)
O_w	Annual O&M costs of wind ($/KW)
O_s	Annual O&M cost of solar ($/KW)
C_s	Capital cost of solar ($/KW)
C_{cap}	Capital cost for CCS (million$/metric tons/hr)
g	Green premium (cent/kWh)
VC	Variable operating cost for CCS ($/MWh)
C_w	Capital cost of onshore wind ($/kW)
CRS	Congressional Research Service
P	Production tax credit (PTC) rate for wind (cent/kWh)
I	Solar Investment tax credit (ITC) rate (% of expenditure)
kWh	Kilowatt-hour
M_{wr}	MARCS rate for wind (%)
CF_{NG}	Natural gas capacity factor (%)
EPA	Environmental Protection Agency
UNFCCC	United Nations Framework Convention on Climate Change
S_{CF}	Solar capacity factor (%)
MACRS	Modified Accelerated Cost Recovery System
CO_2	Carbon dioxide
MWh	Megawatt hour
CCS	Carbon capture and storage
NPV	Net present value
r	Discount rate
Q	Section 45Q tax credit for CCS ($/metric ton of CO_2)
RE	Renewable Energy
EIA	Energy Information Agency
T	The lifespan of the project
U.S	United States
CF_c	Coal capacity factor (%)
W_{CF}	Wind capacity factor (%)
MT	Metric tons
IEA	International Energy Agency
DOE	Department of Energy

decarbonization of the electricity system, there is no guarantee for its economic feasibility in the long term. Thus, the authors recommended additional incentives and a further reduction in the cost of capturing CO_2.

Despite the existence of an increasing number of pilot and demonstration projects for CCS applications in the power sector, commercial adoption that supports a financial return remains very few worldwide (GCCSI, 2021). Hence, there is little historical market data on the actual cost of operating a CCS retrofit. Moreover, there are several uncertainties concerning future costs and output performance of power plants with CCS (Di Lorenzo et al., 2012). As a result, in the past, the literature focused on estimating and predicting the extent and variability of CCS construction and operating costs under different scenarios (Fan et al., 2020a,b). This study contributes to the literature by focusing on the monetization of CCS investments via market and policy-induced incentives. Despite a growing number of studies arguing for leveraging policy incentives for CCS (Waxman et al., 2021) and renewable energy investments (Boomsma et al., 2012; Sendstad and Chronopoulos, 2020), there were no discovered studies that conceptualized and operationalized a market-based approach for incentivizing CCS in the electric power industry. The study fills this gap by presenting a first estimate of the minimum dollar per kilowatt hour (kWh) price premium required to sell electricity generated by power plants with a CCS retrofit, in the presence of an uncertain market, technical, and policy environment. The study also evaluates the cost-effectiveness and economic implications of other approaches, such as performance mandates, technology mandates, status quo versus additional policy incentives, and additional market incentives, for achieving carbon reduction goals in the power sector.

This study extends the frontier of climate technology economics in the electricity sector by studying the impact of uncertainties associated with market, technical, and policy variables on the financial net return of power generators. The stochastic approach was justified for at least three reasons. First, carbon capture is a relatively newer and developing technology with a higher probability of quickly improving production and efficiency parameters. Renewable energies (RE) are known for their variable and less predictable performance outcomes. Second, the long-term continuation of policy and financial support for climate-friendly technologies, such as CCS is not 100% certain and is likely to change with shifting policy focus (e.g., the U.S. pulled out of the emission reduction talks between 2016 and 2020 and later rejoined). Third, as established in the literature the construction and operation costs of CCS are extremely variable and sensitive to the specific capture technology, location, and other contextual factors (Waxman et al., 2021).

Section 2 presents the conceptual framework and quantitative approach used to evaluate the effect of uncertainties in the technical, policy, and market variables on the economic performance for investing in CCS and/or RE technologies to meet a given carbon reduction goal. Section 3 presents the results and discussion. Section 4 presents the conclusions and recommendations for policies and strategies that may improve the adoption of climate technologies.

2. Conceptual framework and methodology

There is a growing number of recent studies that estimate the cost of CCS technologies. Several studies compared the cost of power plants with and without CCS (Rubin et al., 2005; Rubin and Zhai, 2012; Singh et al., 2022). For instance, Rubin and Zhai (2012) studied the levelized cost of electricity (LCOE) for a natural gas combined cycled power plant with and without CCS and the impact of carbon pricing in adopting CCS. The authors concluded that the LCOE of plants with CCS increased with uncertainties, while emission tax or carbon pricing encouraged CCS adoption among new power plants. Other studies such as Lohwasser and Madlener (2012) and Fan et al. (2020a,b) concentrated on the high investment costs in RE and CCS technologies. Rao and Kumar (2014) studied the implications of adding CCS to existing coal plants in India and concluded that the cost of electricity generation increased with CCS.

In the context of China, Zhang et al. (2014) developed a model for comparing the costs of a power plant without CCS retrofit with the pre-investment cost of a CCS retrofit of a second power plant. The effects of carbon pricing and the use of captured carbon for oil recovery were examined to obtain the optimal timing to invest in CCS. Zhang et al. (2014) concluded that the two power plants under study were both not optimal for investment in the current market situation and that the increase in carbon pricing in China will encourage the immediate execution of CCS retrofits. Similarly, studies that argue for carbon pricing to encourage CCS adoption include Mo et al. (2018), Zhang et al. (2014), Zhu and Fan (2013), and Rohlfs and Madlener (2011). Singh et al. (2017) projected the cost of CCS for the next three decades for upcoming coal plants and the implications of carbon pricing on the economic adoption of CCS.

Hamilton et al. (2009) studied the effects of climate policies on the deployment of CCS technologies and concluded that the US carbon cap-and-trade bill would not be enough to deploy CCS technology. Hamilton et al. (2009) argued for the need for a supporting framework including CCS research, development, and demonstration to encourage CCS deployment. In the context of China, Mo et al. (2015) examined the implications of an emission trading system on CCS investments and the abatement of CO_2 and considered the role of CCS flexibility (e.g., running the plant off CCS when the carbon price is low) for new power plants. Mo et al. (2015) apply Monte Carlo simulations to account for carbon price variability and show that CCS operating flexibility lowers the need to have high-carbon prices to stimulate investment in CCS.

This study builds upon existing works that estimated CCS costs and argued for incentive-based policies (e.g., cap and trade) and further expands the literature by providing a framework that shows the economic benefits of using either RE or CCS to produce green energy in an uncertain environment. Secondly, this study does not only compare the costs associated with RE and CCS technologies like previous research works have done but also evaluates the uncertainties with existing incentives and policies for green energy production. This study examines the effects of placing technological mandates on the choice of clean energy and carbon abatement technologies. Finally, a recommendation on how policymakers could encourage power producers to invest in multiple carbon management strategies is provided.

2.1. Alternative approaches for decarbonization

There are two policy approaches for curbing emissions and protecting the environment and these are (i) command-and-control approaches; and (ii) incentive-based mechanisms (Stavins and Whitehead, 1992; Janet Peace Jason Ye, 2020). The command-and-control approach either sets a goal for curbing emissions and allows businesses to choose the technology for compliance or sets a technology mandate without specifying a reduction goal (Stavins and Whitehead, 1992; Aldy and Stavins, 2012). In an incentive-based regime, businesses are incentivized (rather than forced) to achieve an end goal via the use of subsidies, tax credits, carbon pricing, or an emission tax (Janet Peace Jason Ye, 2020). For instance, economic incentives could encourage the adoption of cleaner energy by lowering costs.

This study considered a performance mandate, which reduces carbon dioxide emissions by a given percentage for all power generators. The study considers two scenarios or strategies to meet this performance target and these scenarios correspond to the technology used to reduce emissions. Scenario 1 used a CCS retrofit, and Scenario 2 retired fossil-based plants and replaced them with renewable energy technologies. These scenarios could be interpreted as a technology choice (chosen by the power plant) or a technology mandate (prescribed by a regulator). For instance, 30 US states and the District of Columbia have clean energy standards (United States State Electricity Portfolio StandardsEPS, 2022) where electric power producers are required to generate a percentage of electricity from clean energy sources. For example, New Mexico has a renewable portfolio standard according to which the state must produce 80% carbon-free electricity from renewable sources by 2040 and 100% from zero-carbon resources (National conference of state legislation, 2021). In 2021, Texas achieved its 2025 renewable portfolio standard set to produce about 10,000 MW (MW) of wind energy (National conference of state legislation, 2021). Wyoming has a low-carbon standard bill (State of Wyoming, 2022) with no specific percentage of CO_2 reduction target and timeline. However, Wyoming officials anticipate that CCS could reduce 80% of CO_2 emissions from coal power plants (Bleizeffer, 2022).

Power generators are faced with uncertain market, technical, and policy environments so this study calculated the probability that each scenario would be economically feasible and then identified the major source of risk that leads to the variability of economic performances. Based on the expected economic net returns, the study develops an initial electricity price premium under the assumption that power generators with a CCS could differentiate their products as net-zero electricity. Finally, this study made policy recommendations regarding the cost-effectiveness of the different decarbonization approaches (i.e., through policy incentives, mandates, and/or markets). See Fig. 1 for the conceptual framework of this study.

2.2. Overview of model and assumptions

While the objective of power generators is typically profit maximization or cost minimization, a performance mandate would create a constraint to this objective. Given a performance mandate, firms (i.e., power generators) generally choose the investment option that complies with the mandate and generates monetary returns or minimizes net cost. For the performance mandate, the study uses the current US nationally determined contribution (NDC) goal which is a 52% emissions reduction of the 2005 emissions levels by 2030 (UNFCCC, 2021). The amount of annual CO_2 reduction that corresponds to a 52% reduction of the 2005 emission levels of an average power generating plant was calculated. This was the amount of carbon captured in Scenario 1 via the CCS retrofit. Based on this, the amount of renewable generation required to replace the fossil fuel capacity was estimated for Scenario 2. Wind and solar energies are the selected RE technologies since they are the two fastest-growing renewable sources for electricity generation (Kangas et al., 2021). It was assumed that in Scenario 2, the power generator retired coal and natural gas plants based on the ratios taken from its current energy portfolio.

This study used deterministic and stochastic modeling concepts to

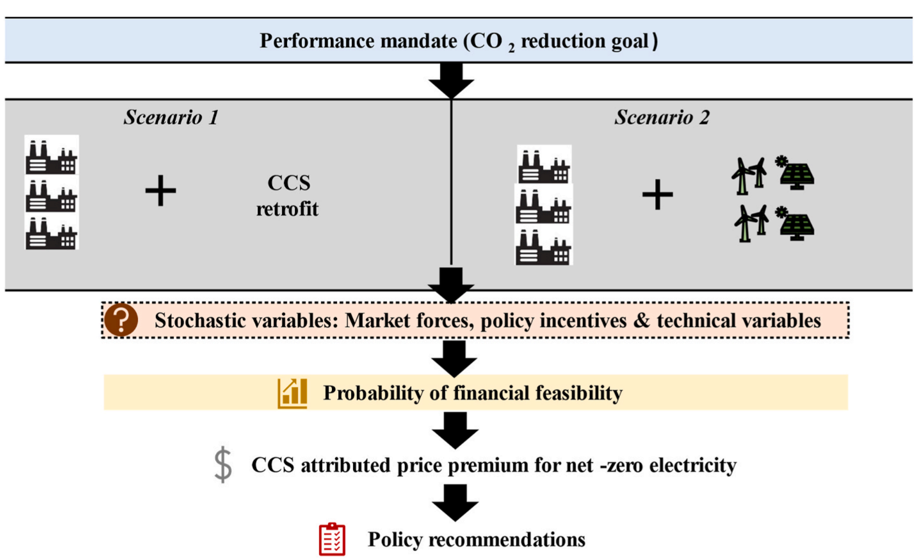

Fig. 1. The conceptual framework for identifying and evaluating policy and market incentives for decarbonizing power using alternative climate technologies.

address the outlined problems. The stochastic modeling, using Monte Carlo simulation, addressed the uncertainties and risks associated with changing markets, technical, and policy variables. The Monte Carlo technique evaluates how individual inputs, sampled from probability distributions in several iterations, affect the economic performance of each scenario (Di Lorenzo et al., 2012). The main performance metric for both deterministic and stochastic models was the net present value (NPV) over a 30-year period, an assumed business tax rate of 21%, and a 5% discount rate. To allow for comparison across scenarios, this study calculated the annualized NPV per metric ton (MT) of carbon dioxide prescribed by the performance mandate.

Table 1 contains a summary of input variables, which comprises of supply-side market variables and costs. The study considered the current market price premium for green electricity as a source of revenue for power generators with renewable technologies. Policy incentives were the types of tax credits available for climate mitigation technologies and the technical variables were production and capacity parameters.

In each model (deterministic and stochastic), when the NPV of a climate technology was negative the study estimated the dollar per kWh needed to break even. This was under the assumption that electricity consumers could differentiate the portion of net zero electricity as a different product (i.e., electricity generated by a plant with CCS retrofit) and hence the product, hypothetically sold in a new market, could command a different price relative to the regular price of electricity. For CCS investments, this value is a first estimate of the price premium that power plants with CCS might need to earn for each unit of electricity with zero carbon emission. This concept was operationalized by calculating the CCS-attributed price premium and comparing it to the current green electricity price premium. Conceptually, one could consider the two products as differentiated from regular electricity retail products, green electricity with zero emissions (or clean), and CCS-attributed electricity with net-zero emissions. As of 2022, there is a market and a price premium for green electricity, but no such market exists for electricity with net-zero emissions achieved via CCS.

The three types of variables (market, technical, and policy variables as in Table 1) contributed to the projected cash flows for 30 years for each scenario. Appendix A presents the mathematical modeling and equations used to arrive at the annualized NPV per MT.

2.3. Overview of Monte Carlo simulations

This study applied Monte Carlo simulation to understand the risks associated with changing market, policy, and technical parameters (Di Lorenzo et al., 2012). The basic steps involved in this simulation were assigning probability distributions for all uncertain variables, drawing random samples from the distribution of each parameter, and performing iterations to produce the number of net benefit realizations (Boardman et al., 2017).

Table 2 shows the distributions used for the various variables. The baseline or initial values and the range of values were taken from a typical power generator in the US. The power producer served an annual load of 0.547 million MWh where 51% of power was produced from fossil fuels (17% from coal, and 34% from natural gas), 36% was produced using renewable energy sources such as wind, solar, and biomass, and 13% was produced from nuclear. The power producer's initial portfolio of renewable energy production was dominated by wind (87%) and solar (12%) (United States Energy Information AgencyEIA, 2021a, United States Energy Information AgencyEIA, 2021b, United States Energy Information AgencyEIA, 2021c).

The annual carbon reduction mandate for the power producer is assumed to be 77,169 MT which is consistent with a 52% carbon reduction goal or target (Yuan et al., 2022). This translates to a fossil fuel reduction amounting to 125,265 MWh per year and replacing it with renewable sources. Appendix B (Tables B1 and B2) contains additional initial values and assumptions used to characterize the typical power generator.

In general, three distributions (asymmetric triangular, bounded-normal, and uniform) were used for the risk analysis. These distributions were used in the literature to evaluate climate mitigation technologies (e.g., Di Lorenzo et al. (2012) proposed the triangular probability distribution for capital cost and normal distribution for prices associated with carbon tax; Li et al. (2018) used the normal distribution for wind power simulation).

The asymmetric triangular distribution was applied to the capital and annual costs of wind and solar energy. The bounded-normal distribution was used for the variable annual cost CCS, and the cost of transporting and storing CO_2. Though the costs of RE and CCs are projected to decline in the future, they will never get to zero. Hence, we bound our simulations to the lowest values obtained in the literature to prevent simulations of zero to negative values. Because the CCS tax credit has only two values since its introduction (i.e., \$50/MT (CRS, 2021) and now \$85/MT (IEA, 2022)), we used the triangular distribution to study the economic impacts with and without the existence of CCS tax credit (e.g., subsidy equal to zero). A total of fifty thousand iterations were run for each scenario.

2.4. Market demand for electricity decarbonization

Aside from the existence of subsidies and tax credits available to renewable energy producers, a green energy market (Bird et al., 2002) is available in the US to maximize investment returns and incentivize the adoption of renewable energy systems (Swezey and Bird, 2001). The green electricity premium is an additional or extra cost that consumers pay for electricity generated from greener and cleaner sources (Swezey and Bird, 2001). Other countries also have green energy pricing. For example, Germany has a green contract where utilities buy RE from green producers and sell it to interested consumers (Bloemers et al., 2001).

The existence of a green price premium indicates that some electricity consumers may be willing to pay more to procure green electricity. Zorić and Hrovatin (2012) and Sharma (2021) showed that households with higher education status, income, and level of

Table 1
Input variables used to calculate net present values.

Technology	Market variables	Technical variables	Policy variables	Model variables
Renewable energy (RE) sources: Wind and solar	• Capital cost • Annual operating and maintenance cost • Costs of retiring fossil fuels • Green electricity premium	• Capacity factors of wind, solar, natural gas, and coal plants • Production share of wind and solar	• Production tax credit for clean energy generation • Investment tax credit for renewable investment • Depreciation tax reduction	• Discount rates • Annuity factor • Inflation rates
Carbon capture and storage (CCS)	• Cost of CCS retrofit • Annual variable cost of operating CCS • Annual cost of storing and transporting	• Carbon capture target • Pipeline capacity	• CCS tax credit	

Table 2
Variables subject to uncertainty, their distributions, and initial and range of values.

Variables	Distribution	Baseline	Range of values	Source
	Market variables			
Capital cost of onshore wind ($/kW)	T (a, b, c)	$1718	$1411 – $3116	United States Energy Information AgencyEIA, 2022
Capital cost of solar ($/kW)	T (a, b, c)	$1327	$1287 – $1612	United States Energy Information AgencyEIA, 2022
Annual O&M cost of wind ($/kW)	T (a, b, c)	$27.57	$32.33 – $64.67	United States Energy Information AgencyEIA, 2022
Annual O&M cost of solar ($/kW)	T (a, b, c)	$15.97	$14.01 – $31.54	United States Energy Information AgencyEIA, 2022
Green electricity premium (cent/kWh)	T (a, b, c)	$0.03	$0.00 – $0.06	United States Environmental Protection AgencyEPA, 2022a, United States Environmental Protection AgencyEPA, 2022b
Capital cost for CCS (million$/metric tons/hour)	N (μ, σ, a, b)	$1.89	$0.69 – $2.48*	Irlam (2017)
Variable operating cost for CCS ($/MWh)	N (μ, σ, a, b)	$5.32	$2.60 – $8.20	Irlam (2017)
Average cost of onshore CO_2 transportation and storage ($/MT)	N (μ, σ, a, b)	$11.40	$4.26 – $14.18*	Schmelz et al. (2020), Irlam (2017)
Inflation rate (%)	U (a, b)	3.27	0.01–7.5	FRED (2022)
Technical variables				
Wind capacity factor (%)	U (a, b)	44	38–55	EIA (2020)
Solar capacity factor (%)	U (a, b)	29	23–36	Lizard (2021)
Natural gas capacity factor (%)	U (a, b)	56	48.6–57.3	EIA (2021a,b)
Coal capacity factor (%)	U (a, b)	55	40.5–60.5	EIA (2021a,b)
Discount rate (%)	U (a, b)	5	2–7	
Policy variables				
Section 45Q tax credit for CCS ($/MT of CO_2)	T (a, b, c)	$50	$0 – $85	CRS (2021), IEA (2022)
Production tax credit (PTC) rate for wind (cent/kWh)	N (μ, σ, a, b)	$1.5	$0.001 – $0.025	US DOE (2021a,b)
Solar investment tax credit (ITC) rate (% of expenditure)	U (a, b)	22	10–30	US DOE (2021a,b)
MARCS rate for wind (%)	U (a, b)	100	0–100	US DOE (2021a,b)

Note: T (a, b, c) = triangular (min, max, mode); U (a, b) = Uniform (min, max); N (μ, σ, a, b) = bounded normal (mean, standard deviation, min, max); * dollar values adjusted to the current year.

environmental awareness are more likely to accept green electricity programs. Grösche and Schröder (2011) performed an internet survey on the willingness to pay for green energy and concluded that willingness to pay for RE electricity generation ranged from 2.05 cents to 2.37 cents per kWh. Sundt and Rehdanz (2015) studied the willingness to pay for green electricity in different regions and found a mean price of 2.49 cents per kWh in the US and 4.43 cents per kWh in Europe. Sundt and Rehdanz (2015) used meta-regression to study people's willingness to pay for RE and concluded that hydropower was the least acceptable because of its consumption of large land acreages with more environmental impact than other RE sources.

Similarly, decarbonization technologies such as CCS could hypothetically command a price premium to create a baseline for investors to patronize these technologies. To make CCS competitive with RE, the establishment of a price premium on net-zero electricity (like that of green electricity premiums) could be a possible market-based solution to accelerate the large-scale adoption of CCS. In this way, power generators with CCS would see more value in investing in CCS technologies. This could potentially be achieved if electricity consumers (e.g., institutional, commercial, residential, etc.) are willing to pay a price premium for the promise of net carbon-free energy alternatives achieved via CCS. However, more studies are needed to study distributional impacts and challenges on implementation.

With CCS technology being a relatively recent technology compared to RE systems, there are uncertainties in costs and subsidies, which create investment decision risks. This study proposed a hypothetical market mechanism whereby CCS-attributed net-zero energy is sold at a price premium to make it profitable for power generators to invest in CCS even in the presence of uncertainties. In other words, the amount of electricity (kWh) that corresponds to the net zero energy due to CCS over the lifetime of the project could potentially earn a price premium.

This proposed price premium was calculated only if the NPVs for the first scenario were negative in either the deterministic or stochastic model. For instance, the price premium ($/kWh) is calculated from Equation (1). Where $NPV_{ccs} < 0$; AF is the annuity factor and E is the net-zero electricity (that is, kWh of electricity equivalent to the MT of carbon reduction performance mandate). See Appendix A.1 for detailed mathematical modeling for this study.

$$\frac{-NPV_{ccs}}{AF\ x\ E} \tag{1}$$

Alternatively, if the NPV was positive, this study estimated $/kWh value of electricity with a net-zero attribute when the power generator had a CCS retrofit (Scenario 1) assuming there is no subsidy. That is, we calculate the equivalent $/kWh to sell CCS-attributed net-zero electricity. This is the same as the value of the CCS subsidy and indicates the fiscal burden of CCS investment. Similarly, when NPV was positive, this study determined the value of technology lifetime cost to understand the $/kWh to cover all costs and break even.

3. Results and discussions

The model was implemented using data obtained from a typical power producer in the US. To meet the performance mandate for reducing carbon emissions by 77,169 MT each year, the power producer has two technological choices. These choices include (1) adopting a CCS retrofit for permanent carbon sequestration to avoid emission to the atmosphere which translates to using status quo production technologies and capturing 77,169 MT of carbon per year (Scenario 1), and (2) retiring fossil production and replacing it with renewable energy production from wind and solar which translates into producing 125,265 MWh of clean energy per year (Scenario 2).

Section 3.1 presents the deterministic model, where all variables are known with 100% certainty. Section 3.2 presents the stochastic model, where the market, policy, and technical variables are random and uncertain. The deterministic and stochastic models generated the economic performance metrics and drew implications for developing a hypothetical; market where CCS-attributable net-zero electricity from Scenario 1 could potentially be sold at a price premium.

3.1. Baseline results: deterministic model

The performance metrics for the deterministic models are shown in Table 3. The results indicate that if power generators are given a carbon reduction mandate but have the liberty to choose the technology to meet the performance mandate, all technologies provide economically feasible outcomes under the given assumptions. RE provided a net return that is approximately 2.6 times that of CCS. This was due to both the market (green electricity market and the green premium) and policy-induced incentives for RE; CCS only had policy-induced incentives.

Besides the costs incurred in developing and operating RE technologies, the cost of retiring existing fossil-based power plants is an additional cost power generators will have to bear. This additional cost does not affect the CCS option in Scenario 1. Moreover, the RE subsidies contributed (MARCS, ITC, and PTC) 32% of the economic return for investing in wind and solar energies, while the green electricity premium contributed 68% of the return. Similarly, CCS tax credits, the only source of monetization of CCS investments, increased annually at the rate of inflation which contributed to a positive NPV for Scenario 1. This result was consistent with the study by Nemet et al. (2015), who concluded that Section 45Q maximizes the returns of CCS investment. The results of this study aligned with Sgouridis et al. (2019), who argued that investing in RE yielded a better energetic return than CCS in the power sector using technical performance metrics of energy return on energy invested (ratio of the energy made available to society over the energy invested in the construction and operation of the power plants). Rather than comparing the net electricity generation from CCS with RE, this study compared the economic performance of investing in the two technologies and found that, under the given assumptions, RE provides a better return than investing in CCS. The fiscal burden of RE is also relatively lower as indicated by the value of RE subsidies, which are 67.5% lower than the value of CCS subsidies ($0.040/kWh versus $0.037/kWh). The private investment costs of RE ($0.037/kWh) are also about 5% lower than the private investment cost of CCS ($0.039/kWh).

Since the only source of monetization of CCS investment is the CCS tax credit provision of Section 45Q subsidy, this study calculated the annualized value of this subsidy as the ratio of the total electricity whose attributable carbon is permanently stored via the CCS retrofit. This yielded a value of $0.04/kWh of electricity, approximately 51% higher than the current value of green electricity premium (electricity from RE sources). This finding suggests that without a CCS subsidy, electricity consumers would have to be willing to pay at least $0.04/kWh for the power generator to be indifferent between receiving the subsidy and charging a price premium to finance its CCS retrofit. Alternatively, if there were no CCS subsidies at all, the power generator would need to receive at least $0.039/kWh to cover the cost of CCS retrofit over the given period.

Table 3
The financial net return of meeting carbon reduction target in deterministic models.

Performance metrics	Power generator's technology choice to meet the performance target	
	Scenario 1 (CCS retrofit to meet 100% target)	Scenario 2 (RE to meet 100% target)
NPV (million)	$2.09	$5.48
Annualized NPV (million)	$0.14	$0.36
Annualized NPV per CO_2 ($/MT)	1.76	4.62
Value of subsidy per kWh	$0.040	$0.013
Value of technology costs per kWh	$0.039	$0.037

The deterministic model results suggested that a CCS technology mandate for the average power generator in this study is not the most cost-effective strategy for addressing the given performance target. Power generators do economically better when they comply with performance standards using RE technologies. Overall, the baseline results suggest that power plants are better off using RE technologies (Scenario 2) than CCS to comply with performance mandates requiring a given percentage reduction in carbon emissions. Given the model assumptions, this is primarily due to market-induced benefits in the form of a green electricity premium for clean energy. Scenario 2 facilitates a lower fiscal burden with a marginally lower private cost compared to the CCS (Scenario 1). Furthermore, without a tax credit, such as Section 45Q, if power generators install a CCS retrofit to comply with the given performance target, they would need to (hypothetically) charge $0.039 per kWh of CCS-attributable net-zero electricity to break even. This price premium is about 47% higher than the green electricity premium.

3.2. Results from stochastic simulations

3.2.1. Scenario 1: impact of uncertainty on CCS retrofit investment

By using CCS to meet the performance target, the power producer's annualized NPV ranged between -$83/MT and $196/MT, with a standard deviation of $40.96/MT, mode and median of $14.22/MT and $18.66/MT, respectively, and a mean of $22.35/MT. Comparing the mean with the deterministic analysis, the mean value obtained in the deterministic model was lower than the value from the stochastic results.

CCS showed more variation in NPV and skewness to positive values than RE (Fig. 2). Close to 69% of the annualized NPV simulated values were positive. The CCS subsidy (Section 45Q) and inflation rate are the two most sensitive variables on the annualized NPV per CO_2 (Fig. 3). With the option of using CCS, the results show that Section 45Q tax credit contributed 57% to the annualized NPV variation of the firm. The inflation rate was the second key parameter that contributed 25%. The annual variable cost, cost of CCS retrofit, and the costs involved in CO_2 storage and transportation contributed 9.6%, 0.6, and 0.3%, respectively (Fig. 4). The discount rate contributed 2% to the variation of annualized NPV per CO_2.

Even though Koelbl et al. (2014) and Budinis et al. (2018) argued that cost uncertainties were key considerations for CCS investment decisions, this study's results showed that monetization via policy incentives is a key strategy for the viability of CCS technology. In this case, the uncertainty arising from the CCS subsidy, the only source of monetization for CCS retrofits, is a key parameter that could affect decision-making (Fig. 5). The annual variable cost of CCS impacted the financial performance of the project negatively. An increase in this variable yielded a steeper negative impact on NPV than the remaining cost variables.

3.2.2. Scenario 2: impact of uncertainty on RE investments

The study presented the effects of changing all input variables concurrently on the annualized NPV per MT of CO_2. The uncertainties involved in using RE to meet the performance target resulted in an average annualized NPV of $0.05 per MT of CO_2. The annualized NPV per MT of CO_2 for the deterministic model ($4.62/MT) was higher than the mean result obtained in the stochastic analysis ($0.05/MT). The range of output from the stochastic analysis was between -$97.8/MT to $80/MT, and it had a standard deviation of $22.01/MT, a mean of $0.05/MT, a mode of $0.56/MT, and a median of $0.30/MT. Approximately 49.5% of the annualized NPV simulated values were negative. The cumulative distribution of the annualized NPV per MT of CO_2 with all uncertain variables is presented in Fig. 6. Comparing the results to the deterministic model, a power producer has a cumulative probability of

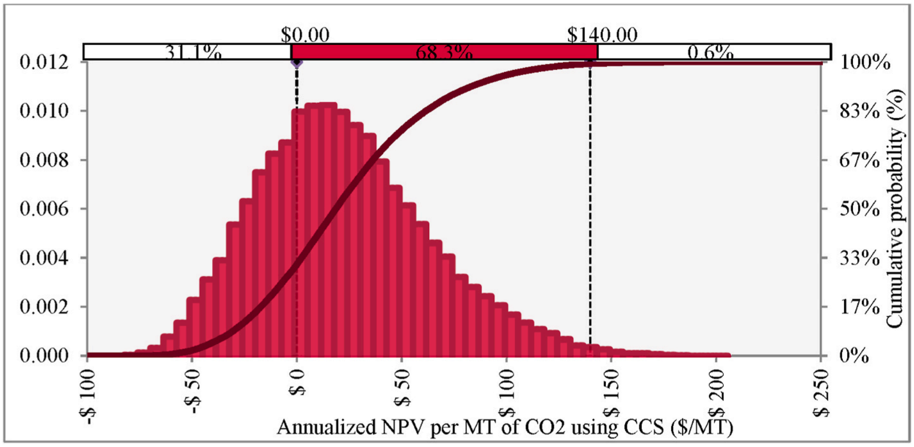

Fig. 2. Probability distribution of NPV for investing in CCS retrofit technology.

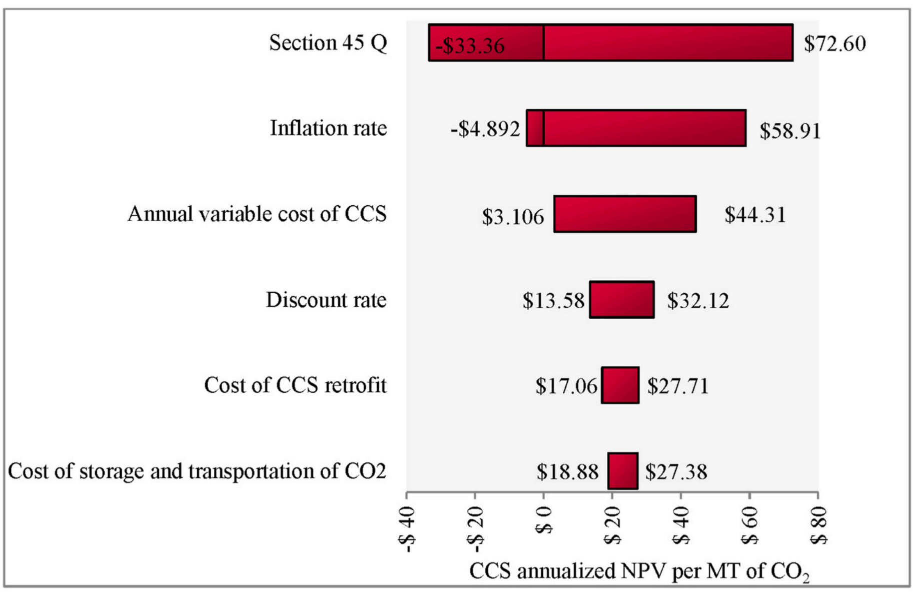

Fig. 3. Impact of variables on the NPV of CCS retrofit technology.

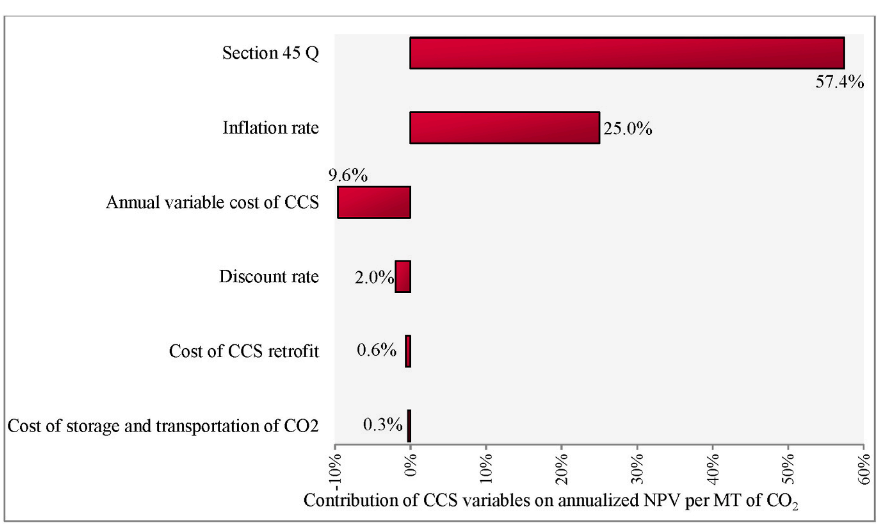

Fig. 4. Contribution of uncertain variables on the variance of annualized NPV.

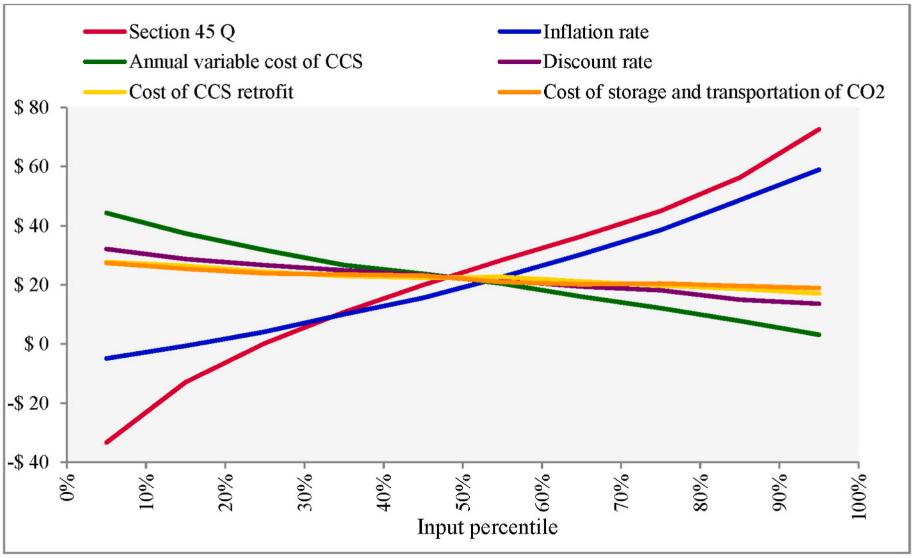

Fig. 5. Effect of changing variables on annualized NPV per MT of CO_2.

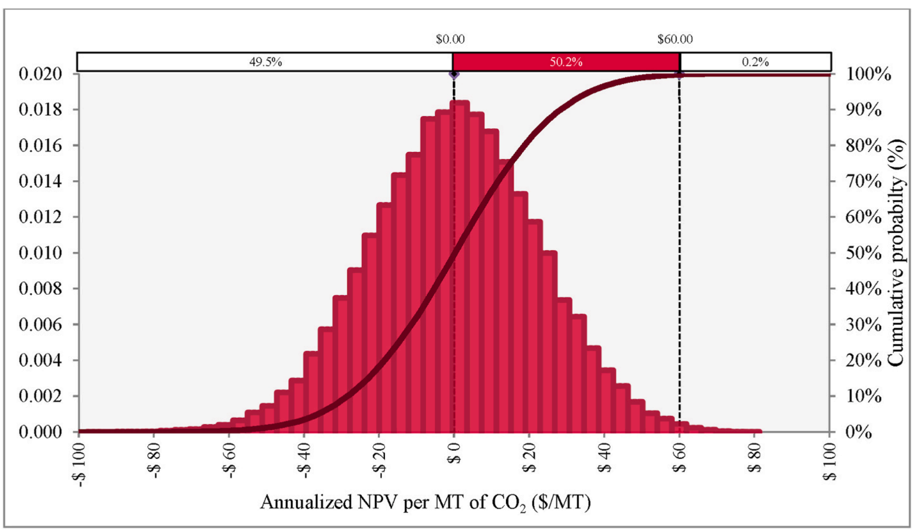

Fig. 6. Histogram and cumulative distribution of financial performance of investing in RE technologies to meet the performance target.

approximately 50% to obtain $4.62/MT or more (Table 3). Thus, uncertainty in input variables affected the feasibility of investing in RE to meet the given performance target.

The risk analysis showed that the annualized NPV, the main economic performance metric for evaluating scenario feasibility, is influenced by the uncertainty from policy variables. This finding is consistent with results from Sendstad et al. (2022), which showed that a stable policy commitment plays a role in RE investments by private firms. The relative impact of uncertainty from policy, market, and technical variables is presented in Fig. 7. The green electricity premium contributed to about 72% of the variations in the annualized NPV, while the capital cost of wind contributed about 11%. The rest of the variables each contribute less than 2% of the variation in the NPV performance (Fig. 8).

Green electricity premium had a strong positive impact on the annualized NPV as seen in Fig. 9. This stresses the importance of market-driven incentives in achieving net-zero or zero-emission goals. As expected, tax credits had a positive impact on NPV. The absence of these policy incentives would likely make the firm run at a loss. This result emphasizes the importance of policy incentives for clean energy investments. Costs have the expected reduction effect on the NPV despite individual cost items not standing out as being relatively stronger.

3.3. Implications for a net-zero price premium

As presented in Section 3.2.1., approximately 31.4% of the simulation runs in Scenario 1 yield negative NPVs. This suggests a high probability of operating at a loss while investing in the CCS technology to comply with performance mandates. This risk level may not encourage investors towards investing in CCS and emphasizes the importance of additional risk-free monetization beyond the provisions from Section 45Q. Such monetization could potentially come from market forces, such as demand for net-zero electricity. Net-zero electricity is generated with retrofitted CCS technology, and thus, the resulting carbon is captured and permanently stored in geological basins. If consumers value net-zero-emission electricity, they might be willing to pay a price premium to reduce the cost of retrofitting CCS technologies in existing power plants.

The price premium to switch negative NPVs to a breakeven point for the stochastic model ranges from a maximum of $0.05 per kWh to a minimum value of $\$2.3 \times 10^{-6}$ per kWh. The associated standard devi-

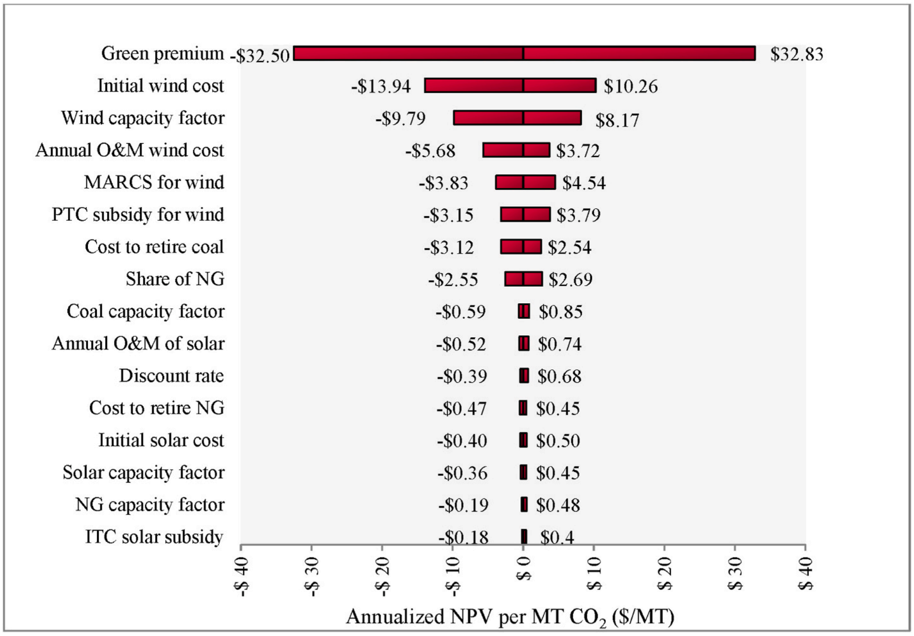

Fig. 7. Impact of individual variables on the variability of financial performance (NG stands for natural gas).

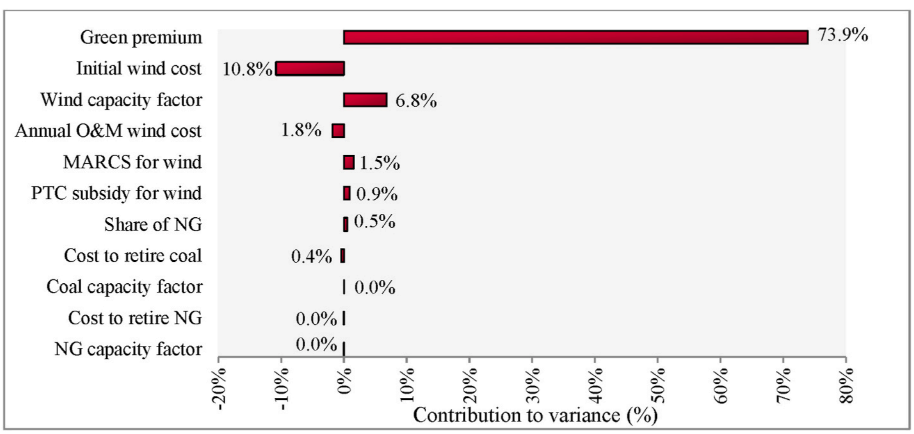

Fig. 8. Impact of uncertain variables on the variance of annualized NPV (NG stands for natural gas).

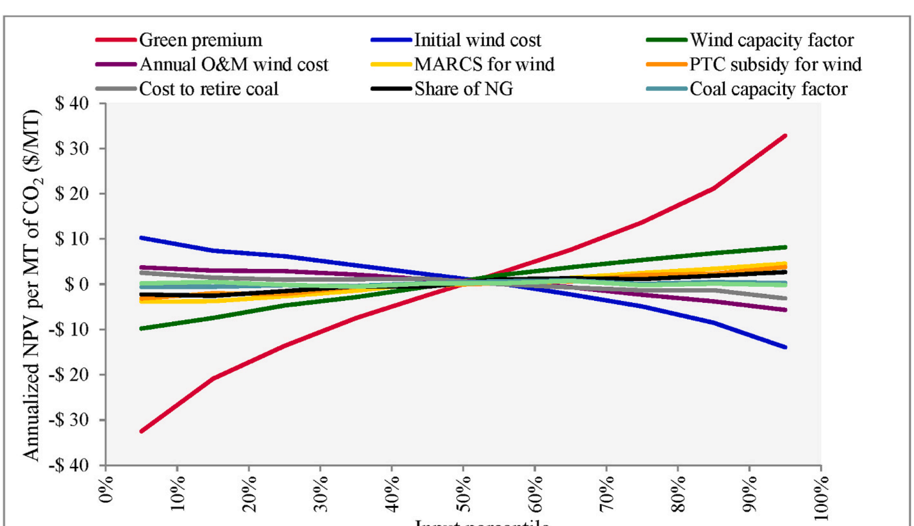

Fig. 9. Effect of changing variables on annualized NPV per MT of CO_2.

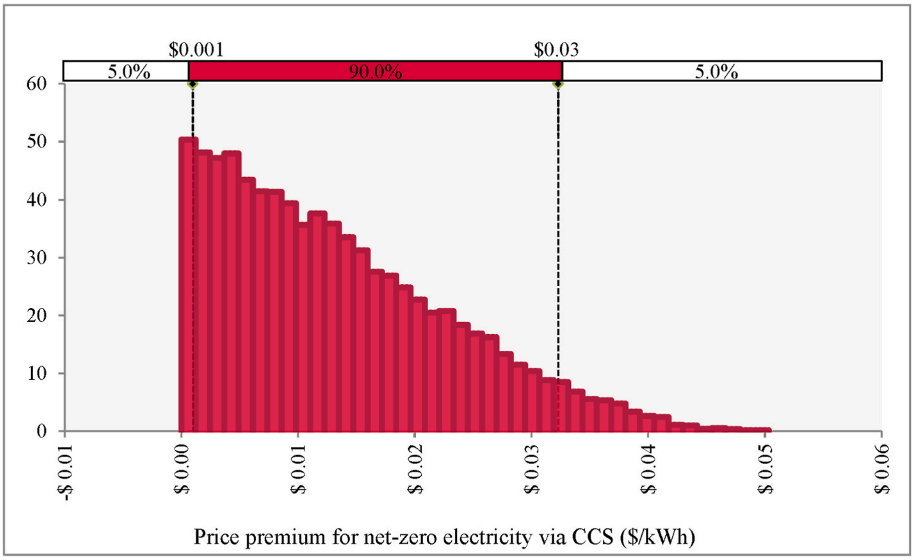

Fig. 10. Results of hypothetical net-zero price premiums for Scenario 1.

ation is $0.01 per kWh, a mean of $0.013/kWh, a mode, and median of $0.001/kWh and $0.011/kWh, respectively (Fig. 10). The mean price premium for Scenario 1 is about 50% less than the existing green premium value of $0.027/kWh for green electricity (United States Environmental Protection Agency, EPA, 2022b). The peak net-zero price premium for CCS is $0.03/kWh, which is the same as the green electricity premium. A price premium of $0/kWh in Fig. 10 corresponds to annualized NPV per CO_2 that yielded a positive NPV value. Thus, it does not need a price premium to break even. See Appendix C.1 for details on CCS subsidy and costs of the net-zero electricity price premium via CCS.

What is the effect of this proposed net-zero price premium for CCS on the consumer? With a hypothetical market featuring a price premium for CCS-attributed net zero electricity, consumers will have to pay an extra up to $0.03/kWh more for electricity. The existing RE market (US DOE, 2022) has consumers paying an extra $0.03/kWh for green electricity and the literature discussed in Section 2 shows the willingness to pay for green electricity. Thus, the proposed price premium for net-zero electricity via CCS from this study is like what consumers are willing to pay for combating climate change and the associated weather and climate catastrophes. However, while we provide an initial estimate for the resulting price premium, we acknowledge distributional impacts need to be examined and carefully considered. In addition, rather than rely on demand forces and willingness to pay, resources could be directed toward research and development to improve the cost performance of existing CCS technologies.

4. Conclusion

This study examined the risks and returns of investing in CCS and RE technologies as alternative strategies to meet a performance target. The uncertainties examined were grouped into policy, market, and technical variables. The metrics for measuring the economic return on investment are the annualized NPV per MT of CO_2. The results from the deterministic model showed that using RE technologies to meet a performance target was a more profitable investment than investing in CCS. The stochastic analysis shows that using either RE or CCS to comply with performance standards was not a risk-free investment.

Table 4 contains a summary of policy recommendations from the study. These recommendations were based on achieving goals using the most cost-effective (generating a positive net return to investors) and risk-reducing path. The results from the deterministic models, which considered the existence of a carbon reduction performance target and the status quo of subsidies and tax credits for climate-friendly technologies (CCS and RE) in the electricity generation sector, indicated the importance of CCS subsidies in the profitability of CCS investment. To encourage the adoption of CCS technologies, CCS subsidies are crucial. The combination of status quo policy incentives (subsidies, tax credits) and green electricity price premiums makes investments in RE profitable. With policies incentives (subsidies and tax credits) but the absence of the green premium yielded an annualized NPV and annualized NPV per MT of CO_2 of -$2.99 million and -$38.80/MT of CO_2 avoided, respectively, highlighting the need for a green electricity market. Therefore, in a deterministic world, the presence of a performance mandate could be cost-effective only with existing policies and market incentives.

Table 4
Policy recommendations.

Recommended approach	Performance mandate with deterministic model	Performance mandate with stochastic model
Status quo policy incentive	Yes	Not enough
Additional policy incentives	No	Yes
CCS mandate	No	No
Green electricity markets	Yes	Yes
Net-zero electricity market	No	Yes

The stochastic modeling approach showed CCS had a wider uncertainty range of annualized NPV per MT of the CO_2 captured and stored than RE. This study showed that the current RE subsidies without the green premium will increase the risk of investment losses in RE. The stochastic model shows that there is a measurable risk in investing in CCS and RE: 31% of NPVs were negative for CCS (Scenario 1) and 49% of NPVs were negative for RE (Scenario 2). An increase in current policy incentives for both RE and CCS as well as the creation of new markets for net-zero electricity from CCS could create opportunities for lowering some of these risks.

A price premium for net-zero electricity achieved via CCS, just like the existing green price premium for RE, could be a potential approach to reduce investors' risk. The price premium for net-zero electricity for power producers who produce electricity, with CCS retrofit technologies, is likely to encourage the adoption of CCS technology globally. This study proposed a net-zero electricity price premium via CCS of at least the current green premium price ($0.027/kWh from EPA, 2022a,b). The proposed CCS-attributed price premium, coupled with Section 45Q, could guarantee at least a break-even point for power plants with CCS retrofits. However, the implementation is more than likely to be challenging and so we recommend future studies to examine the impact of such markets on energy accessibility.

Conclusions drawn from this study include: (1) Carbon reduction mandate (performance target) from global governments requires more efforts to make investments in clean electricity generation. The current subsidies and tax credits for both CCS and RE are not enough with the uncertainties surrounding market, policy, and technical variables. (2) The use of RE to address performance target is cost-effective than using CCS in a deterministic but not necessarily a stochastic model. (3) Policymakers could set carbon reduction targets/mandates for power producers but should not mandate the choice of technologies to meet the emission reduction mandate. Power producers should be allowed to choose technology (clean and/or abatement) that maximizes their profits while producing electricity and meeting the performance mandates set by policymakers.

This study relies on a number of simplifying assumptions and so results could change with changing assumptions and modeling approaches. For example, this study could be improved by considering the effects of depreciation of clean energy and abatement assets over time. Secondly, we used a 21% business tax which may widely vary across time and space. Finally, data is obtained from a generic power generator operating in the US and several numerical values are simulated based on the US market. Future studies could extend the work by looking at other markets where there are more advanced CCS projects.

CRediT authorship contribution statement

Jessica W.A. Azure: Conceptualization, Methodology, Data curation, Formal analysis, Illustration/graphs, Software, Writing – original draft. **Samuel Frimpong:** Conceptualization, Writing – review & editing. **Mahelet G. Fikru:** Conceptualization, Methodology, Writing – review & editing.

Declaration of competing interest

The authors have no personal or monetary interests that could influence the results reported in this paper.

Data availability

All data used is mentioned in the paper

Appendix A

A.1. Mathematical modeling

Equations (2) and (3) show the estimations for the total initial cost incurred for using wind and solar energy. The capital costs are one-time costs incurred in the initial year. All rates for costs for wind and solar are obtained from EIA (2022a,b).

$$TC_s = C_s \times S_C \tag{2}$$

TC_s is the total initial capital cost for solar (\$), C_s is the average capital cost for solar (\$/KW) and S_C is the solar capacity (KW).

$$TC_w = C_w \times W_C \tag{3}$$

TC_w is the total initial capital cost for wind (\$), C_w is the average capital cost for wind (\$/KW) and W_C is the wind capacity (KW).

The costs incurred yearly from solar and wind energy are shown in Equations (4) and (5), respectively. We estimated the operating and maintenance costs as the product of the rate cost in \$/KW and the capacity factor of energy.

$$TO_s = O_s \times S_C \tag{4}$$

TO_s is the annual fixed operating and maintenance cost for solar (\$) and O_s is the average annual rate for fixed operating and maintenance cost for solar (\$/KW).

$$TO_w = O_w \times W_C \tag{5}$$

TO_w is the annual operating and maintenance cost for wind (\$) and O_w is the average annual rate of fixed operating and maintenance cost for wind rate (\$/KW).

Equations (6) and (7) represent the cost of retiring existing fossil-based (natural gas and coal) power plants with RE (wind and solar).

$$TC_c = \frac{C \times (W + S)}{24 \times 365 \times CF_c} \times C_c \tag{6}$$

TC_c is the total cost of retiring coal (\$), C is the share of electricity generated from coal (%), W is the annual wind production (kWh), S is annual solar production (kWh), C_c is the average cost to retire coal (\$/KW) and CF_c is the capacity factor of coal (%).

$$TC_{NG} = \frac{NG \times (W + S)}{24 \times 365 \times CF_{NG}} \times C_{NG} \tag{7}$$

TC_{NG} is total cost of retiring natural gas (\$), NG is share of electricity generation from natural gas (%), CF_{NG} is the capacity factor of natural gas (%) and CF_{NG} is the average cost to retire natural gas (\$/KW).

The costs involved in using CCS as a CO_2 reduction technology include the costs of carbon capture, operating and maintenance (O&M), transport, and storage. The capture cost included the carbon capture equipment, material, labor, and indirect costs associated with capturing CO_2 (e.g., energy penalty cost) obtained from Irlam (2017). The cost of CCS retrofitting is a one-time cost that occurs in the initial year. The O&M cost is the annual cost involved in maintaining the technology (Irlam, 2017). In our model, the costs of transporting and storing CO_2 are considered an annual cost, and the average values of Schmelz et al. (2020) and Irlam (2017) are used as initial values. Equation (8) through (10) indicate the estimation of costs involved in using CCS technology.

$$I_{cap} = C_{cap} \times H \tag{8}$$

I_{cap} is the initial cost of CCS retrofit (\$/MT), C_{cap} is the average cost of retrofitting CCS (\$/MT/hr), and H is the CCS capture target per hour.

$$A_{ST} = CO_2 \times C_{ST} \tag{9}$$

A_{ST} is the annual cost for transporting and storing CO_2 ($), C_{ST} is the average cost of CO_2 transportation and storage ($/MT) and CO_2 is the amount of CO_2 captured annually (MT).

$$A_{VC} = CO_2 \times VC \tag{10}$$

A_{VC} is the annual variable cost of CCS and VC is the variable cost of CCS ($/MWh) capturing the energy penalty cost of a power plant with CCS. The capacity factors of RE estimations are presented in Equations (11) and (12).

$$S_C = \left(\frac{S}{24 \times 365 \times S_{CF}}\right) \tag{11}$$

S_C is the solar capacity (KW), S_{CF} is the solar capacity factor (%), and S is annual solar production (kWh).

$$W_C = \left(\frac{W}{24 \times 365 \times W_{CF}}\right) \tag{12}$$

W_C is the solar capacity (KW), WC_F is wind capacity factor (%), and W is the annual wind production (kWh).

The only source of monetization for CCS is the CCS tax credit called Section 45Q tax credit in the US. CCS tax credits are assumed to annually increase at rate equal to the inflation rate.

$$CCS_S = Q \times CO_2 \times GAF \tag{13}$$

CCS_S is the CCS tax credit ($) earned, CO_2 is the amount of CO_2 captured annually (MT), Q is the rate of Section 45Q subsidy ($/MT). AF is the annuity factor, r = discount factor (%), t = time, and R is the inflation rate. The growing annuity factor and annuity factor are calculated using Equations (14) and (15).

$$\text{Growing annuity factor}, GAF = \frac{(1 - ((1+R)/(1+r)\hat{t}))}{r - R} \tag{14}$$

$$AF = \frac{1 - (1+r)^t}{r} \tag{15}$$

The green electricity price premium for wind and solar energy is a market-based incentive for investing in RE (see Equation (16)). It is calculated as follows:

$$G = g \times (W + S) \tag{16}$$

G is the total annual value of the green premium ($) and g is the green electricity premium ($/kWh). There are three types of policy-induced sources of monetization for RE in the US: production tax credit (PTC) for wind energy generation, investment tax credit (ITC) and depreciation tax reduction for wind and solar equipment referred to as Modified Accelerated Cost Recovery System (MARCS) depreciation (US DOE, 2021a,b). The PTC is a tax credit that is earned for the first 10 years of wind energy generation (US DOE, 2021a,b). The ITC is a one-time credit on the initial dollar amount invested in renewable energy.

$$PTC = P \times W \times AF_{10} \tag{17}$$

PTC is the total production tax credit ($), P is PTC tax credit rate for wind generation ($/kWh), AF_{10} is the annuity factor for 10 years.

$$ITC = I \times S_{C\times}\ C_s \tag{18}$$

ITC is the total investment tax credit for solar ($), I is investment tax credit (ITC) rate for solar (%).

$$M_W = M_{wr} \times TC_w \times B \tag{19}$$

$$M_S = M_{sr} \times TC_s \times B \tag{20}$$

B is the business tax paid by the power operator (%), M_{wr} is MARCS rate for wind energy (%), M_{sr} is MARCS rate for solar energy (%), M_W is MARCS subsidy for wind ($), M_S is MARCS subsidy for solar ($).

A.2. Financial performance metrics

Equation (21) through (24) show the mathematics behind the financial performance metrics for each scenario. The annualized NPV is a measure of the yearly financial return earned from each scenario. This is divided by CO_2 captured (via CCS) or CO_2 avoided (via RE) to get the annualized NPV per MT of CO_2.

Total discounted life-time policy induced incentives for solar and wind energy is calculated in Equation (21).

$$b_{RE} = PTC + M_w + M_s \tag{21}$$

The total discounted market-induced life-time net benefit (A_{RE}) is calculated in Equation (22).

$$A_{RE} = (G - TO_w - TO_s) \times AF_{30} \tag{22}$$

AF_{30} is annuity factor for 30 years. T_{in} is total initial cost net of initial subsidy if any ($) and is calculated in Equation (23).

$$T_{in} = TC_w + TC_s + TC_c + TC_{NG} - ITC \tag{23}$$

The net present value for each scenario is calculated as follows:

$$NPV_{RE} = A_{RE} + b_{RE} - T_{in} \tag{24}$$

$$NPV_{ccs} = CCS_S - (A_{ST} + A_{VC}) \times AF_{30} - I_{cap} \tag{25}$$

Appendix B

B.1. Generation and carbon emissions of the electricity producer modeled in this study

Table B1 shows the energy generation of an average independent power producer (IPP) for Texas. We consider the average IPP in Texas as our case study because the electric power generators in Texas are ideal to study the CCS-RE relationship for at least three reasons. First, the Texas electricity market is deregulated, and thus individual power generators produced about 66% of the total electric power of the State (EIA, 2021a,b). According to PUCT (2022), there are about 580 IPPs in Texas. Second, pre-existing non-utilized oil wells have a good potential for carbon storage (Chaudhry et al., 2013). Medlock and Miller (2020) stated that Texas has a geological formation suitable for storing CO_2. Third, Texas has favorable climatic conditions for wind and solar energy production and is one of the leading states on renewable generation.

The total CO_2 emissions for power sector for 2021 was extrapolated from EIA, 2021a,b. The carbon intensity of fossil energy sources for a typical power producer calculated is shown in Table B2. Finally, the annual CO_2 reduction target that meets a 52% reduction of the 2008 emissions levels of the USA was estimated (Table B2).

Table B.1
Source of electric power generation for the average power producer in 2021 (EIA, 2021a,b)

Energy source	Average generation per producer (MWh)	Percentage (%)
Coal	95,018	17.3
Hydroelectric Conventional	64	0.01
Natural Gas	186,397	34.03
Nuclear	69,330	12.66
Other Biomass	556	0.10
Petroleum	39	0.01
Solar Thermal and Photovoltaic	24,332	4.44
Wind	171,962	31.40

Table B.2
Statistics of CO_2 reduction target and RE of the average IPP used in this study.

Description	Values
The annual generation of power plant (MWh)	547,642
Annual non-renewables needed to replace fossil fuels (MWh)	62,632.643
Annual wind energy production (MWh)	54,869.022
Annual solar energy production (MWh)	7763.621
Carbon intensity of fossil generation of IPP (MT of carbon/MWh)	6.16×10^{-4}
Performance CO_2 reduction target consistent with 52% goal (MT)	77,168.87

Appendix C

C.1. Impacts of CCS subsidy and costs on net-zero price premium via CSS

Figure C1 showed that CCS subsidy has a greater impact on the net-zero electricity price premium. Section 45Q and annual variable cost involved in CCS had a regression coefficient of −1.16 and 0.7, respectively. The cost of retrofitting CCS and cost of storing and transporting CO_2 had a regression coefficient of 0.19 and 0.14, respectively. This results emphases on our conclusions that investors should concentrate on policy subsidies than the costs involved in investing in CCS. As the CCS subsidy increases, the need for the net-zero electricity price premium reduces.

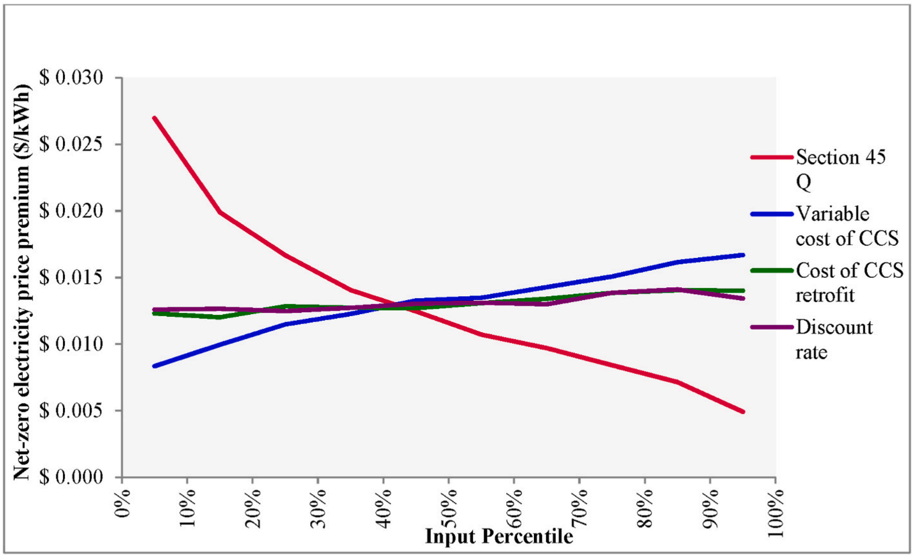

Fig. C.1. Change in the mean of net-zero price premium via CCS across range of input values.

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