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Dynamic Mechanisms of CCS-EOR Technology Diffusion Driven by Carbon Market Policies: An Evolutionary Game Analysis and Carbon Price Threshold Study

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Abstract

Large-scale diffusion of carbon capture, storage, and enhanced oil recovery (CCS-EOR) technology requires coordinated decisions by CO_2 capture and utilization enterprises, yet their economic incentives are interdependent. This study aims to explain how carbon allowance prices and allocation constraints affect bilateral CO_2 pricing and the subsequent adoption of CCS-EOR technology. An alternating-offer bargaining model for determining the CO_2 transaction price is coupled with a two-population evolutionary game describing the adoption decisions of capture and utilization enterprises. This integrated approach examines how carbon-market policies shape bargaining outcomes, economic returns, and adoption strategies of both enterprise types. Four techno-economic scenarios calibrated to Chinese CCS-EOR projects are examined using equilibrium analysis, numerical diffusion simulations, a ±10% parameter sensitivity analysis, and stochastic allowance price robustness tests. The critical allowance prices are 64.9 and 110.0 USD/tCO_2 for low- and high-capture-cost scenarios, respectively, a difference of 45.1 USD/tCO_2 (approximately 69.5% of the low-capture-cost threshold). A ±10% change in operating capture cost shifts these thresholds by ±6.15 and ±10.66 USD/tCO_2, whereas the same change in levelized fixed capture cost shifts both thresholds by ±0.34 USD/tCO_2. Simulations using a 19 × 19 grid of initial adoption probabilities quantify the basin of attraction of joint adoption; the critical carbon price depends on capture costs, while oil recovery benefits and other techno-economic factors affect the diffusion trajectories below the threshold. Robustness analysis is conducted, considering allowance price fluctuations under a mean-reverting process across different noise intensities (σ = 0 and 6 USD/tCO_2). The findings show that carbon pricing influences utilization enterprises indirectly through bargained CO_2 transaction prices and that coupling bilateral price negotiations with evolutionary adoption decisions offers a more comprehensive explanation of CCS-EOR technology diffusion and differentiated policy requirements.

Keywords: CCS-EOR; carbon market policies; technology diffusion

Check for updates

Received: 30 September 2026
Revised: 29 October 2026
Accepted: 3 November 2026
Published: 6 November 2026

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1. Introduction

Amidst dual pressures of global climate governance and energy transition, carbon capture, utilization, and storage (CCUS) technology has emerged as a critical pathway

for achieving low-carbon utilization of fossil fuels. Within this domain, CO_2 enhanced oil recovery (CCS-EOR) technology—which simultaneously delivers carbon abatement and increased oil recovery—has gained significant global attention. However, despite its demonstrable environmental and economic potential, the large-scale deployment of this technology has consistently fallen short of expectations. Current implementation challenges reveal that barriers to diffusion extend beyond technical bottlenecks in isolated segments; more fundamentally, they stem from structural conflicts between economic viability and market entities' decision-making paradigms.

From an economic perspective, CCS-EOR projects exhibit markedly asymmetric cost structures. Research indicates that CO_2 capture and transportation account for 70–80% of total project investment, creating prohibitive economic barriers to technology adoption. Concurrently, cyclical fluctuations in international oil prices and the absence of global carbon pricing mechanisms subject project revenue streams to high volatility. This combination of high upfront costs and unstable returns undermines sustained investment incentives among enterprises.

Notably, the market diffusion mechanism of CCS-EOR technology exhibits unique interdependent dynamics distinct from conventional low-carbon technologies. Effective implementation requires simultaneous adoption by capture enterprises (e.g., power plants, chemical facilities) and utilization enterprises (e.g., oilfields), establishing a stable supply–demand cycle. The economic viability of these enterprises remains intrinsically linked through CO_2 transactions: capture enterprises rely on scale economies from utilization enterprises' CO_2 demand to amortize costs, while EOR productivity gains depend on stable, low-cost CO_2 supply from capture sources. This bidirectional economic interdependence theoretically creates synergistic diffusion logic. In practice, however, it manifests as an adoption deadlock—individual entities cannot overcome the dual constraints of cost burdens and risk exposure to trigger diffusion. Yet, current market mechanisms and policy frameworks lack effective institutional coordination incentives, perpetuating diffusion barriers.

Against this backdrop, carbon policies are widely regarded as pivotal levers for resolving the aforementioned impasse. Globally, governments are advancing concrete measures to deepen the integration of carbon policies with CCS-EOR technology. For instance, in 2024, China's National Energy Administration announced initiatives to explore viable pathways and mechanisms for incorporating CCUS projects into carbon markets. However, under CCS-EOR's inherent interdependence, how carbon policies simultaneously incentivize capture enterprises and utilization enterprises to overcome adoption deadlocks through economic signaling remains inadequately defined. Furthermore, in the absence of clear mechanisms through which carbon policies incentivize CCS-EOR diffusion, determining appropriate policy instruments—specifically, carbon allowance prices and constraints—to facilitate this diffusion remains equally challenging.

This study addresses the mechanisms by which carbon allowance constraints and prices incentivize capture and utilization enterprises to overcome adoption deadlocks. First, we examine how carbon allowance constraints and prices impact the economic viability of CCS-EOR for both capture and utilization enterprises. Building on this foundation, an evolutionary game model is developed to analyze the influence of carbon allowance constraints/prices on adoption willingness, thereby revealing the diffusion mechanisms for CCS-EOR technology. Finally, we construct techno-economic scenarios to simulate CCS-EOR diffusion processes, identifying the requisite carbon allowance price thresholds for diffusion under varying economic conditions. Adopting an interactive perspective of adoption willingness between capture and utilization enterprises, this study elucidates how carbon allowance constraints and prices govern CCS-EOR diffusion dynamics. The findings

establish new research trajectories for subsequent investigations while providing robust support for policy formulation.

2. Literature Review

Current research on carbon pricing's impact on technology diffusion predominantly analyzes how carbon allowance prices affect technological economic feasibility. Studies on CCS-EOR economic viability generally fall into three categories: capture enterprise-focused research, utilization enterprise-focused research, and full-chain assessments. Capture enterprise studies examine cost accounting, investment decisions, and influencing factors of carbon capture installations, concluding that these systems substantially increase capital investment and operational costs, thereby impacting investment decisions [1–3]. Key metrics such as fixed costs, operating expenses, and CO_2 capture volumes are critical for CCS-EOR viability and diffusion [4]. Utilization enterprise research employs cost–benefit modeling and numerical simulation to assess oilfield economics under varying energy prices, production taxes, and carbon allowance prices, showing that EOR profitability depends on oilfield characteristics (recovery rates, storage efficiency) and oil price dynamics [5,6]. However, most oilfields exhibit limited capacity to absorb actual CO_2 capture/processing costs, creating economic adoption barriers [7,8]. Full-chain economic analyses reveal suboptimal economics and high investment risks under current conditions, with required carbon prices for power plant retrofits substantially exceeding prevailing levels [9,10]. Subsequent research integrates carbon allowance prices into CCS-EOR feasibility frameworks, analyzing either system-wide viability or capture enterprise economics specifically [11–14]; these studies collectively indicate that step-change feasibility improvements occur beyond certain carbon price thresholds. Nevertheless, most research on carbon pricing's impact on CCS-EOR feasibility focuses on directly affected capture enterprises or system-wide economics, rarely accounting for the interdependence between capture and utilization enterprises or carbon pricing's indirect effects on utilization enterprises through CO_2 supply–demand dynamics.

Building upon economic feasibility analyses, some studies employ evolutionary game models to examine adoption willingness among and interdependencies between stakeholders (e.g., governments, enterprises, consumers) to reveal technology diffusion mechanisms [13,15,16]. These studies concur that current diffusion remains unattainable without policy support [12,17–19]. Further research incorporates carbon allowance prices into diffusion mechanism analyses to investigate enterprise decisions regarding low-carbon technology adoption under carbon pricing from micro-level perspectives [20,21], ultimately identifying appropriate carbon pricing as the critical leverage point for CCS-EOR diffusion [22–24]. Recent studies adopt more advanced approaches—multi-agent simulation, system dynamics, and complex-network evolutionary games—to model the interdependent adoption of CCUS between heterogeneous stakeholders and network topologies [12–14,16,20,24–26], Multi-agent simulation explicitly represents heterogeneous decision-makers with distinct objectives and information endowments, allowing their rule-based interactions to be traced over time; system dynamics captures aggregate feedback loops among technology cost, market, and policy variables at the macro level; and complex-network evolutionary games embed adoption decisions in explicit network topologies to examine how local connectivity and information diffusion shape global diffusion outcomes. These approaches relax the assumption of homogeneous, well-mixed actors and thus accommodate agent- and network-level heterogeneity, with attention centered on the dynamics of interdependent adoption across these heterogeneous settings. Additional studies employ econometric approaches—notably difference-in-differences—to assess the effectiveness of carbon pricing by comparing low-carbon technology activity between carbon-market pilot and non-pilot regions, reporting stronger innovation incentives where allowance prices or

market turnover are higher, with market turnover exhibiting a stronger stimulative effect than price levels themselves [27,28]. These studies focus on how carbon-price levels and market activity influence aggregate low-carbon technology adoption.

In contrast, this study couples the bilateral bargaining that determines the CO_2 transaction price with a two-population evolutionary game describing technology adoption, and examines how carbon-market policy shapes the bargaining outcomes, economic returns, and adoption strategies of both the capture and utilization enterprises.

3. Method

This section comprises two integrated components: (1) application of a bargaining game model to quantify correlated economic impacts between capture enterprises and utilization enterprises under carbon allowance constraints and prices, and (2) development of an evolutionary game model with capture/utilization enterprises as the primary agents to analyze the dual mechanisms through which carbon allowance constraints and prices govern CCS-EOR diffusion.

3.1. Bargaining Model of CO_2 Transaction Prices

A bargaining game model is employed to determine the transacted CO_2 price between capture enterprises and utilization enterprises. Building on this foundation, we conduct a comprehensive economic viability assessment of CCS-EOR technology from the dual perspectives of both enterprise types.

This study distinguishes between the CO_2 transaction price (P) and the carbon allowance price (AP). P refers to the price negotiated between capture and utilization enterprises for captured CO_2, whereas AP denotes the market price of emission allowances. In this study, AP specifically represents the secondary-market trading price of initially free-allocated carbon allowances, excluding other carbon asset transactions.

The full-chain CCS-EOR process comprises three phases: capture, transportation, and storage. The capture phase is executed by capture enterprises, involving complex costs simplified into two categories: fixed capture cost (unit cost denoted as G_1) and operational capture cost (unit cost C_1). The transportation phase involves moving captured CO_2 to utilization enterprises, with responsibility for bearing the transportation costs (unit cost C_2) yet to be determined between the two entities—responsibility may lie with either capture enterprises or utilization enterprises. This allocation will be explicitly addressed in subsequent sections. The storage phase is managed by utilization enterprises, with costs simplified as fixed storage cost (unit cost G_2) and operational storage cost (unit cost C_3). Additionally, CCS-EOR generates oil displacement revenue from increased crude production, determined by oil displacement rate (r) and oil price (p), thus expressed as r·p per ton of CO_2 stored.

The emergence of carbon markets imposes dual impacts on capture enterprises: First, it establishes emission constraints whereby capture enterprises cannot emit CO_2 without limit; excess emissions beyond government-allocated carbon allowances (W) must be mitigated through either capture measures or purchasing allowances on the carbon market. Second, CO_2 capture generates additional revenue; under carbon market mechanisms, after meeting their own allowance requirements, capture enterprises can sell surplus allowances on the market, yielding carbon market revenue determined by total enterprise emissions (E), government-allocated allowances (W), captured CO_2 traded to utilization enterprises (Q), and carbon allowance price (AP), expressed as $(E-W-Q) \times AP$. When $E-W-Q < 0$, it indicates that after meeting its carbon allowance requirements, an enterprise has surplus carbon allowances to sell on the carbon market. When $E-W-Q > 0$, it indicates that the

enterprise must purchase additional carbon allowances on the carbon market to fulfill its carbon allowance requirements.

The economic benefits of capture enterprises and utilization enterprises are shown in Figure 1.

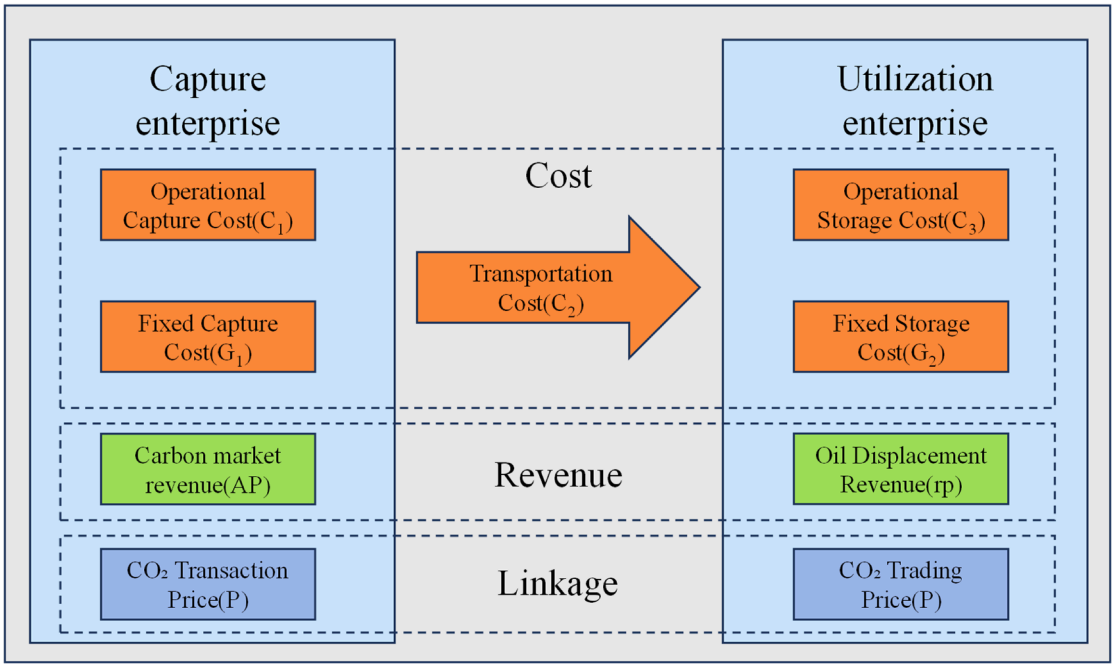


Figure 1. Economic benefit structure of capture enterprises and utilization enterprises under the influence of carbon allowance price.

The selection of a bilateral bargaining model is based on two characteristics of CCS-EOR transactions. First, CO_2 transportation costs generally increase with distance, encouraging capture and utilization enterprises to establish geographically proximate trading relationships rather than relying on a centralized market. Second, enterprises differ considerably in their costs and expected benefits, making a uniform CO_2 transaction price less suitable for individual transactions. Therefore, this study adopts a bilateral bargaining model to examine CO_2 price negotiations between capture and utilization enterprises.

Specifically, the asymmetric Rubinstein bargaining model is employed to represent sequential negotiations and differences in bargaining positions between the two parties. Compared with symmetric bargaining approaches, this model explicitly incorporates alternating offers and different discount factors, allowing the effects of asymmetric waiting costs on negotiated prices to be examined. Under carbon market conditions, capture enterprises face carbon-compliance obligations that may affect their willingness to delay an agreement, while utilization enterprises are assumed to make the first offer. These features provide the economic rationale for adopting the asymmetric bargaining model in this study. The model is developed under the following assumptions:

Assumption 1. *Participants are capture enterprises and utilization enterprises, both of sufficient scale to possess potential adoption willingness for CCS-EOR technology. Their bargaining proposals and decisions reflect industry representativeness.*

Assumption 2. *Both parties maximize self-interest; discount factors are less than unity for both parties, and each prefers concluding the negotiation in fewer rounds.*

Assumption 3. *Under carbon market pressures, capture enterprises face greater constraints; utilization enterprises hold the bargaining advantage, and thus, make the first offer.*

Assumption 4. *Both capture and utilization enterprises operate under complete information [29,30].*

The symbols used in the bargaining and evolutionary game models are summarized in Table 1.

Table 1. Mathematical symbols and their definitions.

Symbol	Definition	Symbol	Definition
AP	Carbon allowance price	P	Negotiated CO_2 transaction price
P_1, P_2, P_3	CO_2 prices proposed in bargaining rounds 1–3	P_c, P_u	Negotiated CO_2 prices when capture and utilization enterprises bear transportation costs, respectively
E	Total CO_2 emissions before capture	W	Allocated carbon emission allowances
Q	Quantity of captured CO_2	C_1	Unit operating cost of CO_2 capture
C_2	Unit CO_2 transportation costs	C_3	Unit operating cost of CO_2 storage
G_1	Levelized fixed cost of CO_2 capture	G_2	Levelized fixed cost of CO_2 storage
r	Oil displacement ratio	p	Crude oil price
rp	Oil recovery revenue per unit of CO_2 utilized	δ_c, δ_u	Discount factors of capture and utilization enterprises, respectively
i	Lending interest rate used to determine the utilization enterprise discount factor	A_1, A_2, A_3	Capture enterprise payoffs in bargaining rounds 1–3
B_1, B_2, B_3	Utilization enterprise payoffs in bargaining rounds 1–3	x, y	Adoption proportions of utilization and capture enterprises, respectively
x_0, y_0	Initial adoption proportions of utilization and capture enterprises, respectively	x*, y*	Critical adoption proportions of utilization and capture enterprises at the interior equilibrium

To explicitly account for disagreement outcomes, we define the disagreement payoffs of capture and utilization enterprises as follows:

$$\begin{cases} d_C = -(E - W)AP \\ d_U = 0 \end{cases} \quad (1)$$

where d_C and d_U represent the respective payoffs when CO_2 transaction negotiation fails.

As previously noted, responsibility for transportation costs (C_2) remains unassigned. We first examine the scenario where utilization enterprises bear C_2.

1. Utilization Enterprises Bear Transportation Costs

Round 1: Utilization enterprises propose an initial CO_2 transaction price P_1. At this price, the economic viability of capture enterprises and utilization enterprises is denoted as A_1 and B_1, respectively, given by Equation (2):

$$\begin{cases} A_1 : (P_1 - C_1 - G_1)Q - (E - W - Q)AP \\ B_1 : (rp - C_3 - C_2 - G_2 - P_1)Q \end{cases} \quad (2)$$

Round 2: If capture enterprises accept the proposal, the negotiation concludes. If they reject, they propose a new CO_2 transaction price P_2. Given discount factors δ_c and δ_u, the economic viability of both parties becomes A_2 and B_2, respectively, as specified in Equation (3):

$$\begin{cases} A_2 : \delta_c[(P_2 - C_1 - G_1)Q - (E - W - Q)AP] \\ B_2 : \delta_u(rp - C_3 - C_2 - G_2 - P_2)Q \end{cases} \quad (3)$$

Round 3: If utilization enterprises accept the proposal, the negotiation concludes. If they reject, they propose a new CO_2 transaction price P_3. The economic viability of both parties then becomes A_3 and B_3, respectively, as specified in Equation (4):

$$\begin{cases} A_3 : {\delta_c}^2[(P_3 - C_1 - G_1)Q - (E - W - Q)AP] \\ B_3 : {\delta_u}^2(rp - C_3 - C_2 - G_2 - P_3)Q \end{cases} \quad (4)$$

The bargaining process continues iteratively until a mutual agreement is reached, forming an infinite-round bargaining game model. Such a model is typically solved via backward induction. Following established methodologies [31], this study designates Round 3 as the induction anchor point for infinite-horizon backward induction.

In Round 3, the net payoffs for capture enterprises and utilization enterprises are A_3 and B3, respectively. According to the subgame perfect equilibrium logic of bargaining models, utilization enterprises will accept a proposal in Round 2 if and only if it satisfies $B_2 \geq B_3$. If $B_2 < B_3$, negotiation inevitably proceeds to the final round. This strategic behavior stems from cumulative attrition effects due to bargaining delays, where opportunity costs grow geometrically with each round. To minimize unnecessary losses and maximize self-interest, rational capture enterprises must adopt a forward-looking pricing strategy in Round 2, where their optimal proposal satisfies $B_2 = B_3$, as formalized in Equation (5):

$$P_2 = (1 - \delta_u)(rp - C_3 - C_2 - G_2) + \delta_u P_3 \quad (5)$$

When the game process reverts to Round 1, the strategic interactions between the two parties exhibit new equilibrium characteristics. If the allocation proposal by utilization enterprises in the first stage yields payoff A_1 for capture enterprises that is less than their anticipated Round 2 payoff A_2, negotiation collapses due to the capture enterprises' strategic rejection, inevitably advancing to Round 2. To prevent escalating attrition costs from prolonged bargaining, rational utilization enterprises must propose an initial allocation satisfying individual rationality constraints: Their optimal strategy simultaneously meets the participation constraint $A_1 \geq A_2$ and maximizes their own payoff. Formally, $A_1 = A_2$, as specified in Equation (6):

$$P_1 = (1 - \delta_c)[C_1 + G_1 + (E - W - Q)AP/Q)] + \delta_c P_2 \quad (6)$$

For infinite-round bargaining models, the equilibrium outcome remains invariant regardless of whether it is initiated in Round 1 or Round 3; thus, $P_1 = P_3$. Through mathematical substitution into Equations (4) and (5), the CO_2 transaction price (Pu) under the scenario that transportation costs are borne by utilization enterprises is derived as shown in Equation (7):

$$P_u = \frac{(\delta_c - 1)[-C_1 - G_1 - (E - W - Q)AP/Q] + \delta_c(1 - \delta_u)(rp - C_3 - C_2 - G_2)}{1 - \delta_c\delta_u} \quad (7)$$

2. Transportation Costs Borne by Capture Enterprises

The CO_2 transaction price (Pc) under the scenario that transportation costs are borne by capture enterprises is solved using Equation (8):

$$P_c = \frac{(\delta_c - 1)[-C_1 - C_2 - G_1 - (E - W - Q)AP/Q] + \delta_c(1 - \delta_u)(rp - C_3 - G_2)}{1 - \delta_c\delta_u} \quad (8)$$

Beyond the participants' cost–benefit structures, the negotiated CO_2 transaction price is also influenced by discount factors, which reflect the economic losses associated with negotiation delays. In the alternating-offer bargaining model, discount factors represent bargaining patience: a higher discount factor indicates greater patience, whereas a lower

discount factor indicates less patience and a greater cost of waiting. When negotiations are delayed, enterprises must postpone expected revenues and investment returns, resulting in opportunity costs. For utilization enterprises, such delays may postpone CO_2 supply and subsequent enhanced oil recovery activities, thereby delaying oil production revenues and increasing the opportunity cost of capital. To quantify negotiation costs, researchers have employed various proxy variables across project types, including negotiation expenses, time costs, GDP growth rates, returns on investment, industry growth rates, and lending rates. Among these, lending rates offer distinct advantages as a measure of negotiation attrition: they reflect the opportunity cost of capital associated with delayed agreements, while the relevant data are readily accessible, objectively measurable, and less susceptible to subjective biases. Therefore, this study adopts the benchmark lending rate n to calculate the discount factor of utilization enterprises [32,33], as expressed in Equation (9). Specifically, n is set at 4.9%, corresponding to the historical five-year benchmark lending rate used for the CO_2 transaction price calculations.

$$\delta_u = \frac{1}{1+n} \tag{9}$$

Unlike utilization enterprises, capture enterprises face carbon-compliance obligations that may increase the economic pressure associated with delayed negotiations. A higher carbon allowance price raises the cost of maintaining uncovered emissions and may reduce capture enterprises' willingness to postpone an agreement. To represent this additional pressure, the ratio of the carbon allowance price (AP) to the unit capture cost ($C_1 + G_1$) is introduced as a dimensionless indicator of carbon-price exposure relative to capture costs. This ratio is incorporated into the discount-rate specification as an additional component of negotiation costs, allowing the discount factor of capture enterprises to decrease as AP increases. The resulting expression is given in Equation (10):

$$\delta_c = \frac{1}{1+n+\dfrac{AP}{C_1+G_1}} \tag{10}$$

In Equation (10), the denominator incorporates two components in addition to unity: the benchmark lending rate (n), representing the opportunity cost of capital, and the ratio $AP/(C_1 + G_1)$, representing carbon-price exposure relative to unit capture costs. The latter serves as a dimensionless proxy for the additional economic pressure associated with negotiation delays under carbon-compliance obligations. Consequently, a higher carbon allowance price reduces the capture enterprise's discount factor, indicating lower bargaining patience. This relationship is consistent with the general principle of bargaining theory that higher delay costs reduce bargaining patience. However, the specific functional form is a modeling assumption rather than an empirically estimated relationship. It provides a tractable representation of how carbon market conditions may influence the capture enterprise's bargaining position.

Subsequent comparative analysis of economic benefits for capture and utilization enterprises under both scenarios yields Equations (11) and (12):

Utilization Enterprises Bear Transportation Costs:

$$\begin{cases} V_c^1 = \left(\frac{(\delta_c-1)[-C_1-G_1-(E-W-Q)AP/Q]+\delta_c(1-\delta_u)(rp-C_3-C_2-G_2)}{1-\delta_c\delta_u}-C_1-G_1\right)Q-(E-W-Q)AP \\ V_u^1 = \left(rp-C_3-C_2-G_2-\frac{(\delta_c-1)[-C_1-G_1-(E-W-Q)AP/Q]+\delta_c(1-\delta_u)(rp-C_3-C_2-G_2)}{1-\delta_c\delta_u}\right)Q \end{cases} \tag{11}$$

Transportation Costs Borne by Capture Enterprises:

$$\begin{cases} V_c^2 = \left(\frac{(\delta_c-1)[-C_1-C_2-G_1-(E-W-Q)AP/Q]+\delta_c(1-\delta_u)(rp-C_3-G_2)}{1-\delta_c\delta_u}-C_1-C_2-G_1\right)Q-(E-W-Q)AP \\ V_u^2 = \left(rp-C_3-G_2-\frac{(\delta_c-1)[-C_1-C_2-G_1-(E-W-Q)AP/Q]+\delta_c(1-\delta_u)(rp-C_3-G_2)}{1-\delta_c\delta_u}\right)Q \end{cases} \quad (12)$$

The differences in net payoffs for capture and utilization enterprises between the two scenarios yield Equation (13):

$$\begin{cases} V_c^1 - V_c^2 = 0 \\ V_u^1 - V_u^2 = 0 \end{cases} \quad (13)$$

It is evident that whether transportation costs are borne by capture enterprises or utilization enterprises does not affect the net payoffs of either entity, nor does it influence CCS-EOR technology diffusion. Consequently, subsequent analyses will proceed under the scenario where utilization enterprises bear the transportation costs.

3.2. Evolutionary Game Model

Evolutionary game theory integrates game-theoretic analysis with dynamic evolutionary processes to elucidate equilibrium formation. Unlike classical game theory—which assumes perfect rationality and common knowledge, an assumption that is often misaligned with reality and neglects dynamic convergence pathways—this approach emphasizes how agents reach equilibrium through trial and error. Its foundations derive from biological evolution, translating "variation, selection, inheritance" into economic "innovation, selection, diffusion." By assuming bounded rationality and modeling decisions via imitation, learning, and mutation, evolutionary game theory overcomes classical game theory limitations. As an established analytical framework for studying interdependent adoption willingness in technology diffusion, it is applicable to examining carbon pricing's impact on CCS-EOR diffusion through strategic interactions between capture enterprises and utilization enterprises.

Based on established research, this study adopts the following assumptions:

Assumption 5. *Utilization enterprises and capture enterprises constitute two distinct populations. Each has two behavioral strategies: adopt technology or not adopt technology. Utilization enterprises choose adoption with probability x and non-adoption with probability 1 − x. Capture enterprises choose adoption with probability y and non-adoption with probability 1 − y.*

Assumption 6. *The system comprising both entities is treated as an integrated whole. Individuals within this system exhibit bounded rationality with learning capabilities, possessing autonomous behavioral strategies and decision-making rights.*

The payoff matrix between utilization enterprises and capture enterprises is constructed as shown in Table 2. The bold text in the payoff matrix distinguishes the strategy choices of capture and utilization enterprises, highlighting the strategic interactions between the two parties.

Table 2. The payoff matrix between utilization enterprises and capture enterprises.

Utilization Enterprises \ **Capture Enterprises**	**Adopt**	**Not Adopt**
Adopt	$(rp - C_3 - C_2 - G_2 - P)Q$, $(P - C_1 - G_1)Q - (E - W - Q)AP$	$-G_2Q$, $-(E - W)AP$
Not Adopt	0, $-(C_1 + G_1)Q - (E - W - Q)AP$	0, $-(E - W)AP$

When both parties adopt CCS-EOR technology, their economic payoffs follow the outcome derived from the bargaining game model in Section 3.1. If utilization enterprises

adopt but capture enterprises reject, capture enterprises avoid G_1 and C_1 expenditures but incur carbon allowance procurement costs; meanwhile, utilization enterprises' G_2 investment constitutes a strategic cost. When capture enterprises adopt but utilization enterprises reject, utilization enterprises avoid costs but forfeit oil displacement revenue $(r \cdot p)$, while capture enterprises bear the operational/fixed capture costs $(C_1 + G_1)$ for CO_2 capture with no transaction counterpart, though they gain revenue from selling surplus carbon allowances. Under non-adoption by both parties, utilization enterprises receive zero payoff, while capture enterprises bear the full carbon allowance procurement costs.

Let U_0^1 and U_0^2 denote the expected payoffs for utilization enterprises choosing adoption and non-adoption, respectively, and $\overline{U}_0$ represents the population average payoff. This yields Equation (14):

$$\begin{cases} U_0^1 = y[(rp - C_3 - C_2 - G_2 - P)Q] - (1-y)G_2Q = (rp - C_3 - C_2 - P)Qy - G_2Q \\ U_0^2 = 0 \\ \overline{U}_0 = x[(rp - C_3 - C_2 - P)Qy - G_2Q] \end{cases} \tag{14}$$

Let U_1^1 and U_1^2 denote the expected payoffs for capture enterprises choosing adoption and non-adoption, respectively, and $\overline{U}_1$ represents the population average payoff. This yields Equation (15):

$$\begin{cases} U_1^1 = x[(P - C_1 - G_1)Q - (E - W - Q)AP] + (1-x)[-(C_1 + G_1)Q - (E - W - Q)AP] \\ \qquad = xPQ - (C_1 + G_1)Q - (E - W - Q)AP \\ U_1^2 = x[-(E - W)AP] + (1-x)[-(E - W)AP] = -(E - W)AP \\ \overline{U}_1 = y\{xPQ - (C_1 + G_1)Q - (E - W - Q)AP\} + (1-y)[-(E - W)AP] \\ \qquad = y[xPQ - (C_1 + G_1)Q + APQ] - (E - W)AP \end{cases} \tag{15}$$

When an individual in the utilization or capture enterprise population chooses adoption, it generates an expected payoff. When comparing this expected payoff with the population average payoff, if the former exceeds the latter, adoption represents a superior strategy, and its proportion increases within the population; if the former is lower, the adoption proportion decreases; if the two are equal, evolutionary equilibrium is reached—termed an equilibrium point.

In evolutionary game models, replicator dynamics equations typically solve for equilibrium points. Following Malthusian dynamic principles, the replicator dynamics for the strategic interactions between utilization and capture enterprises are given by Equation (16):

$$\begin{cases} \dfrac{\mathrm{Dx}}{\mathrm{dt}} = \mathrm{x}(\mathrm{U}_0^1 - \overline{\mathrm{U}}_0) = \mathrm{x}(1-\mathrm{x})[(rp - C_3 - C_2 - P)\mathrm{y}Q - G_2Q] \\ \dfrac{\mathrm{Dy}}{\mathrm{dt}} = \mathrm{y}(\mathrm{U}_1^1 - \overline{\mathrm{U}}_1) = \mathrm{y}(1-\mathrm{y})[\mathrm{x}PQ - (C_1 + G_1)Q + APQ] \end{cases} \tag{16}$$

The Malthusian dynamics equation quantifies the differential between the expected payoff of adoption and the population average payoff. When this equation exceeds zero, it indicates that adoption yields higher expected returns than the population average. Mathematically, the magnitude of the Malthusian dynamics is determined by technological costs, revenues, and the initial adoption probability—defined as the proportion of adopters within each population at the evolution's outset.

The equilibrium points derived thus far are merely local equilibria and may lack stability. Even if evolution reaches such points, the system may not remain there but continue evolving. Stability must therefore be rigorously verified. According to Friedman's local stability criterion based on the Jacobian matrix (denoted F), a local equilibrium qualifies as an evolutionarily stable strategy (ESS) if and only if it satisfies the conditions in Equation (17):

$$\mathrm{F} = \begin{Bmatrix} \frac{\partial \mathrm{x}'}{\partial \mathrm{x}} & \frac{\partial \mathrm{x}'}{\partial \mathrm{y}} \\ \frac{\partial \mathrm{x}'}{\partial \mathrm{x}} & \frac{\partial \mathrm{y}'}{\partial \mathrm{y}} \end{Bmatrix} = \begin{Bmatrix} \mathrm{a}_{11} & \mathrm{a}_{12} \\ \mathrm{a}_{21} & \mathrm{a}_{22} \end{Bmatrix} \tag{17}$$

where $x' = dx/dt$ and $y' = dy/dt$, as shown in Equations (18) and (19).

$$\text{Condition1} : \det F = \begin{vmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{vmatrix} = a_{11} \times a_{22} - a_{12} \times a_{21} > 0 \quad (18)$$

$$\text{Condition 2: } \mathrm{tr}F = a_{11} + a_{22} < 0 \quad (19)$$

4. Discussion

4.1. Economic Viability of CCS-EOR Technology Diffusion Under Carbon Markets

The total economic revenue (V) of CCS-EOR technology diffusion under carbon markets is quantified by Equation (20):

$$V = V_c^1 + V_u^1 = (rp - C_1 - C_2 - C_3 - G_1 - G_2)Q - (E - W - Q)AP \quad (20)$$

When (E−W−Q)AP > 0, government-allocated carbon allowances (W) plus captured CO_2 volumes (Q) remain insufficient to cover actual emissions (E). Capture enterprises must purchase additional allowances, thus increasing their costs and reducing the economic viability of CCS-EOR technology diffusion. This negative feedback effect constitutes a financial barrier to technology diffusion. Conversely, when (E−W−Q)AP < 0, a carbon allowance surplus generates dual economic incentives: direct revenue from carbon trading and enhanced project economics through carbon asset accumulation.

Carbon markets directly affect capture enterprises but not utilization enterprises. However, industrial chain transmission mechanisms link both entities through CO_2 transaction prices (P), which reflects both capture enterprises' cost structures (including carbon market factors) and utilization enterprises' economic constraints. Capture enterprises embed carbon price impacts into their pricing strategies, transmitting policy effects to utilization enterprises through the bargaining processes. Ultimately, carbon markets indirectly influence utilization enterprises via transaction prices, completing the effect transmission from policy endpoints to industrial terminals.

From the CO_2 transaction pricing mechanism perspective, carbon market policy signals reshape industrial chain bargaining dynamics by altering capture enterprises' decision parameters. Specifically, the carbon allowance price (AP), as the core policy variable, significantly reduces capture enterprises' patience threshold during negotiation—when carbon cost pressures transmit to transaction quotas, capture enterprises face urgent cost-recovery needs, elevating their time preference rate and diminishing their discount factor. This psychological shift directly weakens capture enterprises' persistence in prolonged bargaining, allowing utilization enterprises to gradually gain pricing advantage. As bargaining power tilts toward utilization enterprises, downward flexibility in CO_2 transaction prices expands, ultimately forming a pricing mechanism more favorable to utilization enterprises and completing the economic transmission of carbon policy effects to industrial terminals.

4.2. Impact Mechanism of Carbon Markets on CCS-EOR Technology Diffusion

4.2.1. Evolutionarily Stable Strategy

The ESS of the evolutionary game model is solved per the aforementioned methodology. First, solving the replicator dynamics equations by setting $dx/dt = 0$ and $dy/dt = 0$ yields five system equilibrium points:

(0,0): Utilization enterprises and capture enterprises do not adopt, leading to technology diffusion failure;

(0,1): Utilization enterprises do not adopt, but capture enterprises adopt;

(1,0): Utilization enterprises adopt, but capture enterprises do not adopt;

(1,1): Utilization enterprises and capture enterprises adopt, leading to technology diffusion success;

(x^*,y^*): Utilization enterprises adopt with probability x^*, and capture enterprises adopt with probability y^*.

Stability analysis of these local equilibrium points follows Friedman's local stability criterion. The key parameter values at local equilibrium are shown in Table 3.

Table 3. Parameter values at local equilibrium.

	a_{11}	a_{12}	a_{21}	a_{22}
(0,0)	$-G_2Q$	0	0	$-(C_1 + G_1)Q + APQ$
(0,1)	$(rp - C_3 - C_2 - P - G_2)Q$	0	0	$(C_1 + G_1)Q - APQ$
(1,0)	G_2Q	0	0	$(P - C_1 - G_1)Q + APQ$
(1,1)	$-(rp - C_3 - C_2 - P - G_2)Q$	0	0	$-[(P - C_1 - G_1)Q + APQ]$

Among these, at point (x^*,y^*), $a_{11} + a_{22} = 0$, violating Equilibrium Condition 2. Thus, (x^*,y^*) cannot possibly be an evolutionarily stable strategy. Therefore, only the other four system equilibrium points are analyzed hereafter.

1. (0,0): Utilization enterprises and capture enterprises do not adopt, leading to technology diffusion failure

Equilibrium Conditions 1 and 2 at (0,0) are given by Equation (21):

$$\begin{cases} -G_2Q \times [-(C_1 + G_1)Q + APQ] > 0 \\ -G_2Q + [-(C_1 + G_1)Q + APQ] < 0 \end{cases} \quad (21)$$

The solution is

$$C_1 + G_1 > AP \quad (22)$$

From an evolutionary game perspective, Equation (22) reveals the critical carbon pricing constraint for technology adoption: the strategy profile (0,0) constitutes an evolutionarily stable equilibrium point if and only if the carbon market price (AP) is lower than the sum of operational capture cost (C_1) and fixed capture cost (G_1). This policy threshold implies that when carbon trading costs persistently undercut CCS-EOR lifecycle costs, capture enterprises develop a strictly dominant strategy—regardless of utilization enterprises' decisions, their optimal choice is always to forgo CCS-EOR investment and meet compliance obligations through allowance purchases. When capture enterprises collectively choose non-adoption, utilization enterprises' optimal response is likewise non-adoption, ultimately driving the system toward technology diffusion failure.

Without carbon market influences, Equilibrium Conditions 1 and 2 hold unconditionally. Thus, in the absence of carbon policies, technology diffusion failure remains perpetually evolutionarily stable. For both entities, non-adoption avoids potential risks despite forfeiting greater benefits, making it the safest strategy regardless of their counterparties' decisions.

Further analysis confirms that the total carbon allowance quotas (W) do not affect whether diffusion failure constitutes an ESS, but carbon price (AP) is the decisive factor. This demonstrates carbon pricing's superior effectiveness over quota allocation controls in driving CCS-EOR technology diffusion.

2. (0,1): Utilization enterprises do not adopt, but capture enterprises adopt

Equilibrium Conditions 1 and 2 at (0,1) are given by Equation (23):

$$\begin{cases} (rp - C_3 - C_2 - P - G_2)Q \times [(C_1 + G_1)Q - APQ] > 0 \\ (rp - C_3 - C_2 - P - G_2)Q + [(C_1 + G_1)Q - APQ] < 0 \end{cases} \quad (23)$$

The solution is

$$\begin{cases} rp - C_3 - C_2 - P - G_2 < 0 \\ C_1 + G_1 - AP < 0 \end{cases} \quad (24)$$

Stability analysis of game equilibria reveals the following: When utilization enterprises' net payoff from adoption is negative and carbon allowance price (AP) exceeds the sum of operational capture cost (C_1) and fixed capture cost (G_1), the strategy profile (0,1) constitutes an evolutionarily stable equilibrium. Under negative net payoff, utilization enterprises' optimal strategy is non-adoption. For capture enterprises, when technology investment costs ($G_1 + C_1$) are lower than A, adopting CCS-EOR technology remains a strictly dominant strategy even if utilization enterprises choose non-adoption.

In the absence of carbon market influences, Equilibrium Conditions 1 and 2 cannot hold. Thus, without carbon policies, the outcome of non-adoption by utilization enterprises and adoption by capture enterprises cannot be evolutionarily stable. Without carbon markets, capture enterprises lack the option to purchase allowances; when utilization enterprises reject adoption and self-adoption yields negative payoffs, capture enterprises' optimal decision is non-adoption.

Evolutionary game theory acknowledges the theoretical possibility of utilization enterprise non-adoption/capture enterprise adoption, but real-world constraints fundamentally prevent it. Without the presence of utilization enterprises for CO_2 storage, capture enterprises must independently process captured CO_2—either through geological storage or alternative utilization. However, these alternatives exhibit inferior techno-economics compared with EOR. This reality traps the (0,1) strategy in a "theoretically possible, practically infeasible" paradox.

3. (1,0): Utilization enterprises adopt, but capture enterprises do not adopt

   Equilibrium Conditions 1 and 2 at (1,0) are given by Equation (25):

$$\begin{cases} G_2Q \times [(P - C_1 - G_1)Q + APQ] > 0 \\ G_2Q + [(P - C_1 - G_1)Q + APQ] < 0 \end{cases} \quad (25)$$

   Equilibrium Conditions 1 and 2 cannot be satisfied, rendering the strategy profile (0,1) incapable of becoming an evolutionarily stable strategy.

4. (1,1): Utilization enterprises and capture enterprises adopt, leading to technology diffusion success

   Equilibrium Conditions 1 and 2 at (1,1) are given by Equation (26):

$$\begin{cases} -(rp - C_3 - C_2 - P - G_2)Q \times [-(P - C_1 - G_1)Q - APQ] > 0 \\ -(rp - C_3 - C_2 - P - G_2)Q + [-(P - C_1 - G_1)Q - APQ] < 0 \end{cases} \quad (26)$$

   The solution is

$$\begin{cases} rp - C_3 - C_2 - P - G_2 > 0 \\ P + AP - (C_1 + G_1) > 0 \end{cases} \quad (27)$$

   For technology diffusion success to evolve as a stable strategy, two core conditions must hold: utilization enterprises' oil displacement revenue must exceed the sum of operational storage cost (C_3), fixed storage cost (G_2), transportation costs (C_2), and CO_2 transaction price (P) (i.e., their unit storage net revenue remains positive); concurrently, the combined value of CO_2 transaction price (P) and carbon allowance price (AP) must surpass the operational capture cost (C_1) and fixed capture cost (G_1) (i.e., capture enterprises' unit capture net revenue remains positive). Equation (27) demonstrates that carbon markets significantly lower the barrier to achieving equilibrium through dual incentives for both entities.

   For utilization enterprises, carbon markets indirectly strengthen their adoption willingness by suppressing CO_2 transaction price (P). Although their revenue–cost function

remains unchanged, carbon markets' price discovery mechanism drives down the CO_2 transaction price. Lower prices reduce technology adoption costs while relaxing the required compensation thresholds for oil displacement revenue, creating a dual beneficial effect: cost reduction + revenue threshold relaxation.

For capture enterprises, carbon markets restructure their revenue streams by introducing income from trading allowances. Under carbon markets, capture enterprises can monetize surplus allowances generated by CCS-EOR technology implementation, yielding additional revenue. This increment directly improves the cost–benefit ratios. When carbon allowance price (A) and CO_2 transaction price (P) form a superimposed effect, capture enterprises' economic boundaries for adoption undergo fundamental optimization, weakening their resistance to technology diffusion.

4.2.2. Final Evolutionary Outcome

When there is only one evolutionarily stable strategy, the final evolutionary outcome is undoubtedly that strategy. However, when there are two evolutionarily stable strategies—(0,0) technology diffusion failure and (1,1) technology diffusion success—it is difficult to determine which evolutionarily stable strategy is the final evolutionary outcome. The discussion will be further expanded below.

When Equation (22) holds and Equation (27) does not hold, the evolutionary game has only technology diffusion failure as the evolutionarily stable strategy. At this point, the final evolutionary outcome is technology diffusion failure. When Equation (22) does not hold and Equation (27) holds, the evolutionary game has only technology diffusion success as the evolutionarily stable strategy. At this point, the final evolutionary outcome is technology diffusion success. When Equations (22) and (27) hold simultaneously, the evolutionary game model has two evolutionarily stable strategies: technology diffusion failure and technology diffusion success. This situation will be further discussed below.

Substitute the proportion of individuals (x, y) (initial adoption probability) adopting CCS-EOR technology among the utilization and capture enterprises in the initial state of the evolutionary game into the Malthusian dynamic equation. If the equation result is greater than 0, it indicates that at this initial adoption probability, the decision to adopt the technology can bring higher benefits than the average benefit of the entire population. Therefore, more enterprises will choose to adopt the technology, and the evolutionary game evolves towards technology diffusion success. If the equation result is less than 0, it indicates that at this initial adoption probability, the expected benefit of choosing to adopt the technology will be less than the average benefit of the population. At this point, more enterprises will choose not to adopt the technology, and the evolutionary game evolves towards technology diffusion failure. Therefore, when technology diffusion success and technology diffusion failure exist as evolutionarily stable strategies, the final evolutionary outcome of the evolutionary game depends on the economic benefit structure of CCS-EOR technology adoption and the initial adoption probability.

Solving the Malthusian dynamic equation yields Equation (28):

$$\begin{cases} y > \dfrac{G_2}{rp - C_3 - C_2 - P} \\ x > \dfrac{C_1 + G_1 - AP}{P} \end{cases} \tag{28}$$

The initial adoption probability represented by Equation (28) is termed the initial adoption probability threshold. When the initial technology adoption probability of capture enterprises $y > \frac{G_2}{rp - C_3 - C_2 - P}$, the expected benefit for utilization enterprises choosing adoption surpasses the population average benefit, leading to an increase in the number of individuals selecting the adoption strategy. Conversely, when the initial technology adoption

probability of utilization enterprises $x > \frac{C_1+G_1-AP}{P}$, the expected benefit for capture enterprises choosing adoption surpasses the population average benefit, leading to an increase in adopters. Therefore, successful technology diffusion is the final evolutionary outcome when Equation (28) is satisfied. Conversely, unsuccessful technology diffusion (failure) is the final evolutionary outcome when it is not satisfied. The final outcome for cases where (x, y) straddles the threshold (one above and one below) will be discussed subsequently.

A smaller initial adoption probability threshold facilitates easier technology diffusion, indicating higher adoption willingness among enterprises. Notably, the threshold x for utilization enterprises corresponds to the adoption willingness of capture enterprises, while the threshold y for capture enterprises corresponds to the adoption willingness of utilization enterprises.

4.3. Carbon Price Threshold for Successful Technology Diffusion Under Different Scenarios

4.3.1. Simulation Scenarios

Based on real-world data from CCS-EOR projects in China, this study constructs a dual-dimensional scenario framework encompassing high/low costs and high/low benefits to simulate the diffusion process of CCS-EOR technology. The aim is to identify the carbon quota price threshold required to drive the large-scale application of this technology.

Currently, the development of CCS-EOR technology in China has accelerated significantly. The accumulated project data now provides systematic support, offering a solid empirical foundation for related research. Domestic deployment has formed a CCS-EOR project portfolio covering multiple source types, including chemical plants, natural gas processing plants, cement plants, and coal-fired power plants. This heterogeneity manifests in the gradient of capture costs resulting from differences in gas source characteristics and variations in technical parameters, such as the CO_2–oil displacement ratio (EOR efficiency), across different oilfields. Leveraging these data characteristics, this study establishes four groups of representative enterprise combination scenarios. By developing a dual-dimensional cost–benefit analysis framework, it comprehensively characterizes the actual operating conditions of different enterprise combinations during the technology diffusion process, providing an empirical foundation for subsequent mechanism analysis.

The cost parameters are derived as follows: Capture, transport, and EOR costs are sourced from China CCUS Annual Reports [34–36]. High/low capture cost scenarios reflect gas source variability. The fixed capture cost (G_1) is estimated based on the benchmark investment cost of 278 USD/kW of installed capacity reported in [37], which is converted to 3.4 USD/tCO_2 by considering a 20-year equipment lifespan and the carbon emission intensity of Chinese coal-fired power plants. The fixed storage cost (G_2), primarily covering CO_2 compression equipment and injection wells, is set at 0.5 USD/tCO_2 based on field research, considering the lower investment costs of retrofitted wells compared with new construction. The CO_2–oil displacement ratios (r) from the same reports cluster around 0.2 and 0.4, defining low/high benefit scenarios. The price parameters use the 2024 crude benchmark (80 USD/bbl), converted via a density factor (7.3 bbl/t) to 587 USD/t. The integration of these parameters yields a CCS-EOR techno-economic matrix (high/low capture costs × high/low benefits) shown in Table 4.

Additionally, the government carbon allowance allocation and the CO_2 capture volume require specification. The total carbon allowance allocation within carbon markets exhibits significant regional variation. Referencing current regulatory frameworks, this study sets an intermediate value for the total carbon allowance allocation at 95 percent. Current CO_2 capture technologies can achieve capture rates exceeding 90 percent of emissions. Accordingly, this study sets the capture volume at 90 percent of carbon emissions.

Table 4. Scenarios of high/low capture costs and high/low oil displacement benefits.

Unit: USD/tCO_2	Operational Capture Cost (C_1)	Transportation Costs (C_2)	Operational Storage Cost (C_3)	Fixed Capture Cost (G_1)	Fixed Storage Cost (G_2)	Oil Displacement Revenue (rp)
Low capture costs–high oil displacement benefits (LH)	61.5	6.8	8.2	3.4	0.5	233.6
Low capture costs–low oil displacement benefits (LL)	61.5	6.8	8.2	3.4	0.5	116.8
High capture costs–high oil displacement benefits (HH)	106.6	6.8	8.2	3.4	0.5	233.6
High capture costs–low oil displacement benefits (HL)	106.6	6.8	8.2	3.4	0.5	116.8

4.3.2. Carbon Price Threshold Calculation

Combining the dual-dimensional scenarios encompassing high/low costs and high/low benefits, this study calculates the requisite carbon price for achieving CCS-EOR technology diffusion under each distinct scenario.

As analyzed previously, successful technology diffusion emerges as the final evolutionary outcome in two contexts: (1) when successful technology diffusion is the sole evolutionarily stable strategy (ESS), and (2) when both successful and unsuccessful technology diffusion exist as evolutionarily stable strategies, yet the system ultimately evolves toward successful technology diffusion.

1. Low Capture Cost–High Oil Displacement Benefit Scenario

(1) Successful Technology Diffusion as the Sole Evolutionarily Stable Strategy

When successful technology diffusion constitutes the sole evolutionarily stable strategy (ESS), the condition specified in Equation (29) must be satisfied:

$$\begin{cases} C_1 + G_1 < AP \\ rp - C_3 - C_2 - P - G_2 > 0 \\ P + AP - (C_1 + G_1) > 0 \end{cases} \quad (29)$$

Solving this equation yields

$$AP > 64.9 \quad (30)$$

Thus, when the carbon allowance price exceeds 64.9 USD/tCO_2, successful technology diffusion is achieved in the low capture cost–high oil displacement benefit scenario.

(2) Coexistence of Unsuccessful and Successful Technology Diffusion as Evolutionarily Stable Strategies

When unsuccessful and successful technology diffusion coexist as evolutionarily stable strategies (ESSs), their coexistence is characterized by Equation (31):

$$\begin{cases} C_1 + G_1 > AP \\ rp - C_3 - C_2 - P - G_2 > 0 \\ P + AP - (C_1 + G_1) > 0 \end{cases} \quad (31)$$

Solving this equation yields

$$0 < AP < 64.9 \quad (32)$$

Under the low capture cost–high oil displacement benefit scenario, the requirement for the carbon allowance price in this context is zero.

As analyzed previously, when two evolutionarily stable strategies coexist, the final evolutionary outcome—given that other conditions are fixed—is determined by the initial technology adoption probability. Successful technology diffusion occurs when the initial adoption probability exceeds the initial adoption probability threshold. However, a specific case exists where one variable (x or y) exceeds its threshold while the other falls below its threshold; the final evolutionary outcome in this scenario cannot be directly determined.

To examine the diffusion dynamics and evolutionary outcomes of CCS-EOR technology adoption, numerical simulations are conducted based on the evolutionary game model. The effects of carbon allowance price on technology diffusion are further investigated by considering four representative price levels (AP = 0, 20, 40, and 60 USD/tCO_2) within the range of 0–64.9 USD/tCO_2. The simulation results are presented in Figure 2.

For Figures 2–5, the horizontal axis (x) represents the proportion of utilization enterprises adopting CCS-EOR technology, while the vertical axis (y) represents the proportion of capture enterprises adopting the technology. The evolutionary trajectories start from different initial conditions and evolve toward their corresponding equilibrium states. Specifically, (0, 0) represents diffusion failure, where neither type of enterprise adopts CCS-EOR technology, whereas (1, 1) represents successful diffusion, where both types of enterprises adopt the technology.

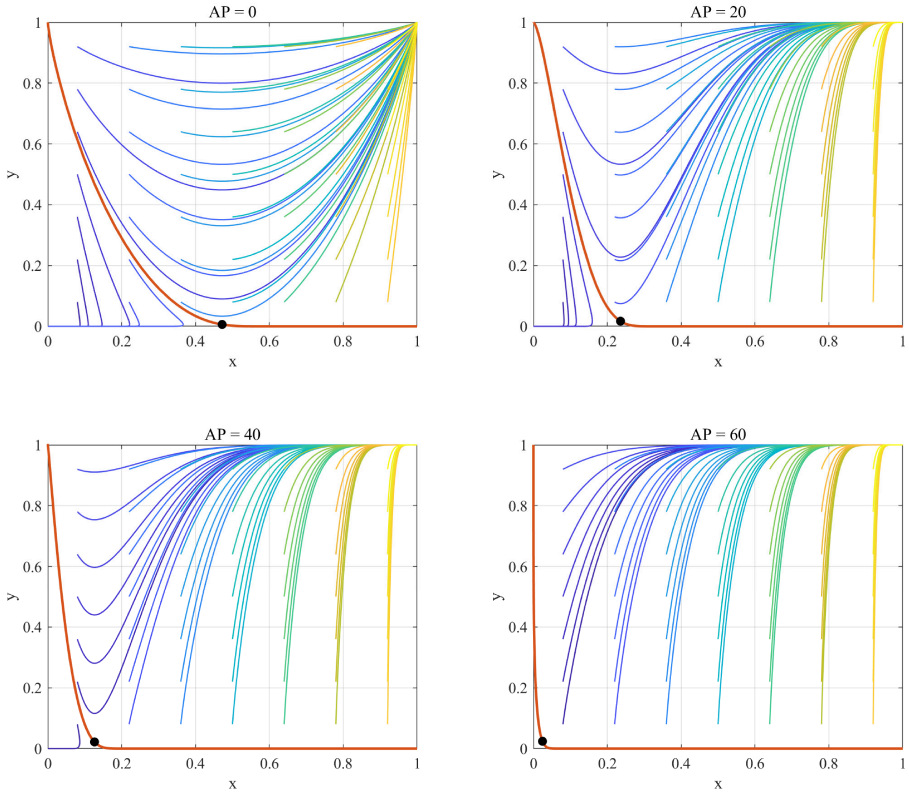


Figure 2. Simulations of technology diffusion under varying carbon allowance prices in the low capture cost–high oil displacement benefit scenario. The colored curves represent evolutionary trajectories under different initial conditions, and the black dots indicate equilibrium points.

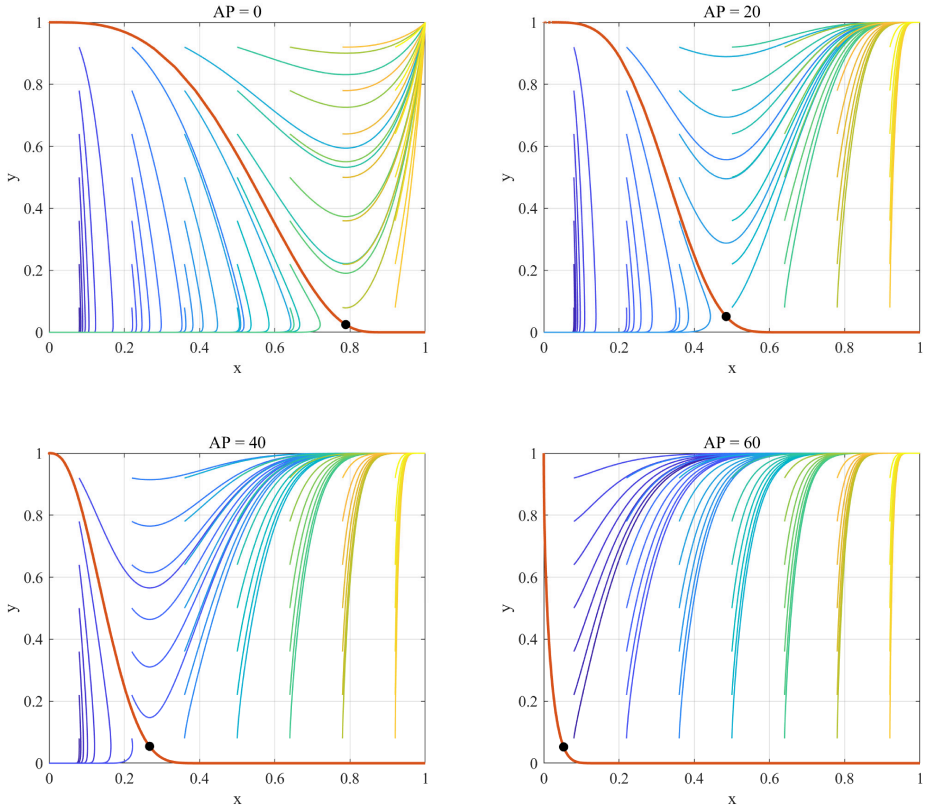


Figure 3. Simulations of technology diffusion under varying carbon allowance prices in the low capture cost–low oil displacement benefit scenario. Notation as in Figure 2.

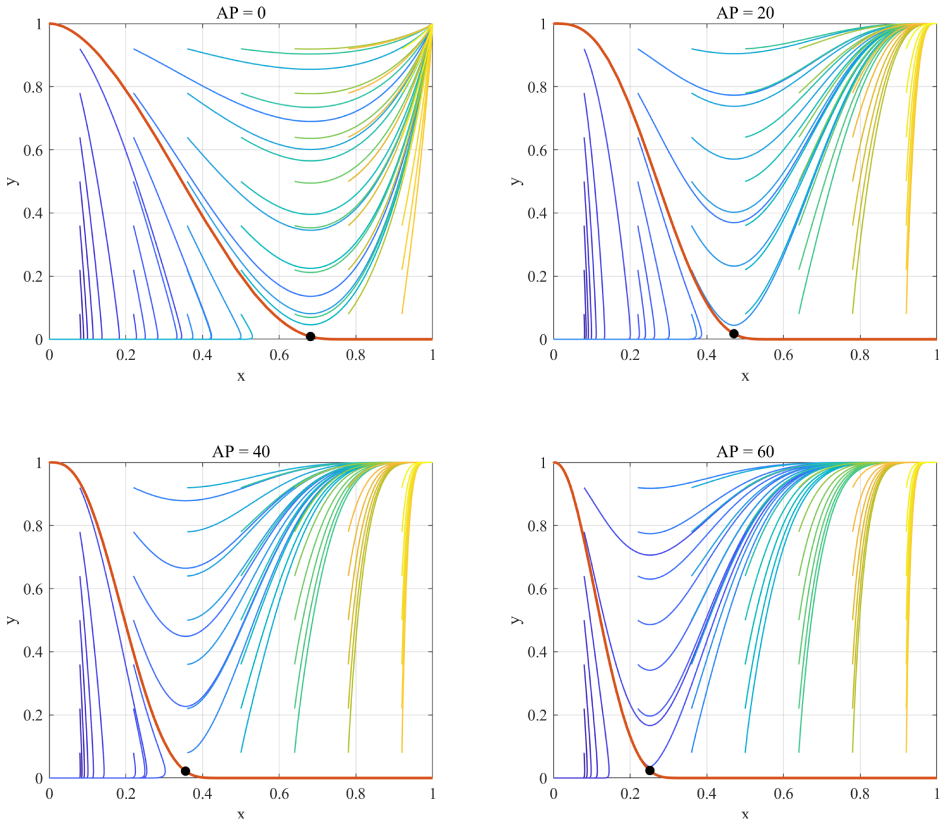


Figure 4. Simulations of technology diffusion under varying carbon allowance prices in the high capture cost–high oil displacement benefit scenario. Notation as in Figure 2. High Capture Cost–Low Oil Displacement Benefit Scenario.

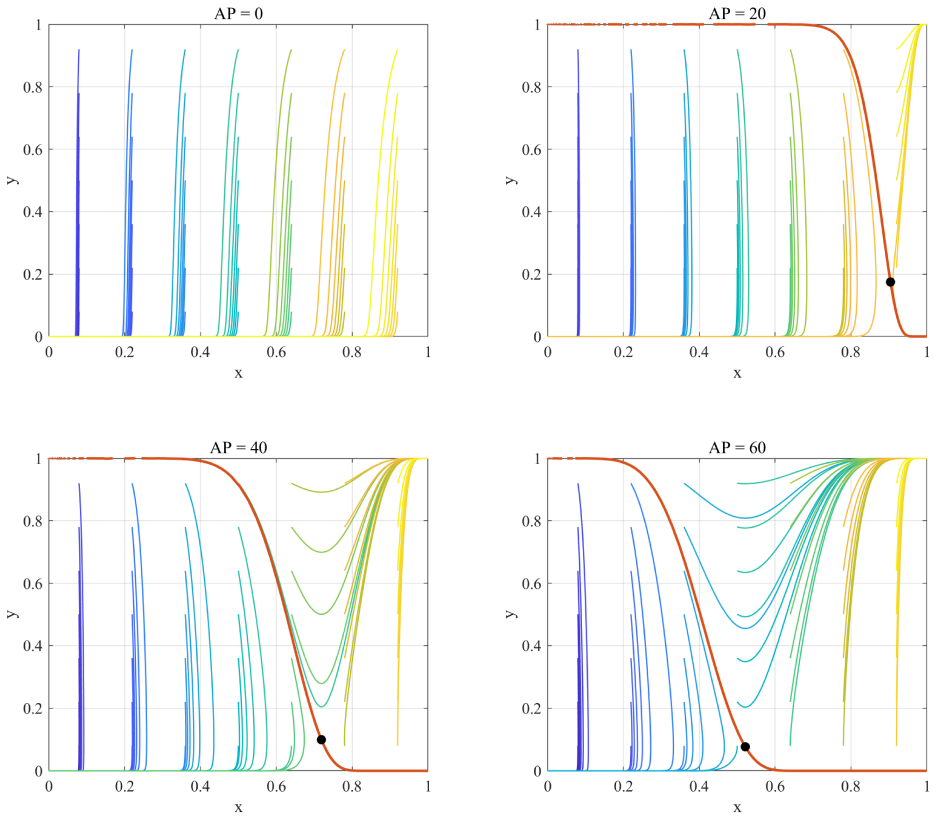


Figure 5. Simulations of technology diffusion under varying carbon allowance prices in the high capture cost–low oil displacement benefit scenario. Notation as in Figure 2.

An analysis of the figure shows that when one variable of the initial adoption probability (x or y) exceeds its threshold while the other falls below its threshold, both variables asymptotically approach the adoption probability threshold. For example, given an adoption probability threshold (x_1, y_1) and initial state (x, y), where $x > x_1$ and $y < y_1$, x gradually decreases while y gradually increases, converging toward (x_1, y_1). When x reaches x_1 first while $y < y_1$, the system evolves toward technology diffusion failure. When y reaches y_1 first while $x > x_1$, the system evolves toward successful technology diffusion. A distinct critical boundary exists between the initial adoption probabilities leading to diffusion failure versus success; initial probabilities above this boundary lead to successful diffusion, while those below result in diffusion failure. Comparative analysis shows that increasing the carbon allowance price significantly shifts the critical boundary downward. This indicates that a higher carbon price substantially reduces the initial adoption probability required for successful diffusion, thereby promoting CCS-EOR technology diffusion.

Furthermore, regarding changes in the critical boundary, increasing the carbon allowance price decreases its slope. This demonstrates that carbon allowance price has a greater impact on the initial adoption probability threshold for x, indicating that it more directly and significantly affects the adoption willingness of capture enterprises compared with utilization enterprises. This occurs because carbon allowance price directly affects capture enterprises while indirectly influencing utilization enterprises.

2. Low Capture Cost–Low Oil Displacement Benefit Scenario

(1) Successful Technology Diffusion as the Sole Evolutionarily Stable Strategy

When successful technology diffusion constitutes the sole evolutionarily stable strategy (ESS), solving the equation yields

$$AP > 64.9 \quad (33)$$

Thus, when the carbon allowance price exceeds 64.9 USD/tCO_2, successful technology diffusion is achieved in the low capture cost–low oil displacement benefit scenario.

(2) Coexistence of Unsuccessful and Successful Technology Diffusion as Evolutionarily Stable Strategies

When unsuccessful and successful technology diffusion coexist as evolutionarily stable strategies (ESSs), solving the equation yields

$$0 < AP < 64.9 \tag{34}$$

The simulation results under different carbon allowance prices for this scenario are presented in Figure 3.

It is observed that under identical carbon allowance prices, the initial adoption probability threshold for CCS-EOR technology diffusion in the low capture cost–low oil displacement benefit scenario is higher than that in the low capture cost–high oil displacement benefit scenario. This indicates that the adoption willingness of capture enterprises and utilization enterprises in the low capture cost–low oil displacement benefit scenario is lower than in the low capture cost–high oil displacement benefit scenario. Thus, high oil displacement benefits significantly enhance the adoption willingness of enterprises.

3. High Capture Cost–High Oil Displacement Benefit Scenario

(1) Successful Technology Diffusion as the Sole Evolutionarily Stable Strategy

When successful technology diffusion constitutes the sole evolutionarily stable strategy (ESS), solving the equation yields

$$AP > 110.0 \tag{35}$$

Therefore, when the carbon allowance price exceeds 110.0 USD/tCO_2, successful technology diffusion is achieved in the high capture cost–high oil displacement benefit scenario. It is evident that the carbon price requirement for successful technology diffusion under high capture costs is substantially higher than under low capture costs.

(2) Coexistence of Unsuccessful and Successful Technology Diffusion as Evolutionarily Stable Strategies

When unsuccessful and successful technology diffusion coexist as evolutionarily stable strategies (ESSs), solving the equation yields

$$0 < AP < 110.0 \tag{36}$$

It is evident that high capture costs significantly increase the upper limit of the carbon price range when two evolutionarily stable strategies coexist. Correspondingly, simulations of the technology diffusion process under different carbon allowance prices are conducted. To maintain consistency with the preceding analysis, four carbon price levels are similarly selected for investigation: AP = 0, AP = 20, AP = 40, and AP = 60. The results are illustrated in Figure 4.

The initial adoption probability threshold under the high capture cost–high oil displacement benefit scenario is greater than that in the low capture cost–high oil displacement benefit scenario. The adoption willingness of enterprises in the high capture cost–high oil displacement benefit scenario is lower than in the low capture cost–high oil displacement benefit scenario. Thus, high capture costs diminish enterprises' adoption willingness.

(1) Successful Technology Diffusion as the Sole Evolutionarily Stable Strategy

When successful technology diffusion constitutes the sole evolutionarily stable strategy (ESS), solving the equation yields

$$AP > 110.0 \tag{37}$$

When the carbon allowance price exceeds 110.0 USD/tCO_2, successful technology diffusion is achieved in the high capture cost–low oil displacement benefit scenario.

(2) Coexistence of Unsuccessful and Successful Technology Diffusion as Evolutionarily Stable Strategies

When unsuccessful and successful technology diffusion coexist as evolutionarily stable strategies (ESSs), solving the equation yields

$$8.1 < AP < 110.0 \quad (38)$$

Unlike previous scenarios, in the high capture cost–low oil displacement benefit scenario, the lower bound of the carbon allowance price range for coexisting evolutionarily stable strategies is no longer zero.

The lower limit of this carbon allowance price range is determined by the total costs of capture, transport, and storage versus the oil displacement benefits. Specifically, a greater difference between the total costs of capture, transport, and storage and the oil displacement benefits corresponds to a higher lower bound for the carbon allowance price range.

Following the established methodology, simulations are conducted at four carbon price levels: AP = 0, AP = 20, AP = 40, and AP = 60.

The results are presented in Figure 5.

It is evident that under the high capture cost–low oil displacement benefit scenario, the initial adoption probability threshold is significantly higher than in other scenarios. Furthermore, when the carbon allowance price equals zero, the evolutionary game invariably progresses toward technology diffusion failure.

Analysis of the four scenarios reveals the following: Under the low capture cost–high oil displacement benefit, low capture cost–low oil displacement benefit, high capture cost–high oil displacement benefit, and high capture cost–low oil displacement benefit scenarios, successful technology diffusion is guaranteed when the carbon allowance prices exceed 64.9, 64.9, 110.0, and 110.0 USD/tCO_2, respectively. When the carbon allowance prices fall within (0, 64.9), (0, 64.9), (0, 110.0), and (8.1, 110.0) USD/tCO_2, respectively, successful technology diffusion requires specific initial adoption probabilities. Therefore, lower carbon allowance prices demand more stringent probability requirements.

4.3.3. Sensitivity Analysis

To assess the sensitivities of CCS-EOR technology diffusion to model parameters, each parameter is varied by ±10% around its baseline value (Table 3), while the remaining parameters are held constant. The analysis considers the critical carbon allowance price and the basin of attraction of the successful diffusion equilibrium (1,1).

The basin-of-attraction share is estimated from a uniform grid of initial adoption probabilities, x and y ∈ {0.05, 0.15, ..., 0.95}, by integrating the replicator dynamics to t = 150. It is calculated as $B(AP) = N_{11}(AP)/N$, where N is the number of sampled initial states and $N_{11}(AP)$ is the number of trajectories that converge to (1,1). Figure 6 shows the estimated basin share at varying carbon allowance prices. Because this measure is based on a finite grid, a value of one means that all sampled initial states converge to (1,1).

The analytical threshold condition also clarifies the parameter sensitivity. A ±10% change in operational capture cost (C_1) shifts AP* by ±6.15 USD/tCO_2 in the low-capture-cost scenario and by ±10.66 USD/tCO_2 in the high-capture-cost scenario. A ±10% change in fixed capture cost (G_1) shifts the threshold by ±0.34 USD/tCO_2. Other parameters do not enter AP* directly under $AP^* = C_1 + G_1$, although they may affect the evolutionary trajectories and the basin of attraction below the threshold.

To focus the numerical analysis on the critical region, Table 5 lists the carbon allowance prices defined as proportional deviations from each scenario-specific threshold; these values are simulation settings rather than simulated outcomes.

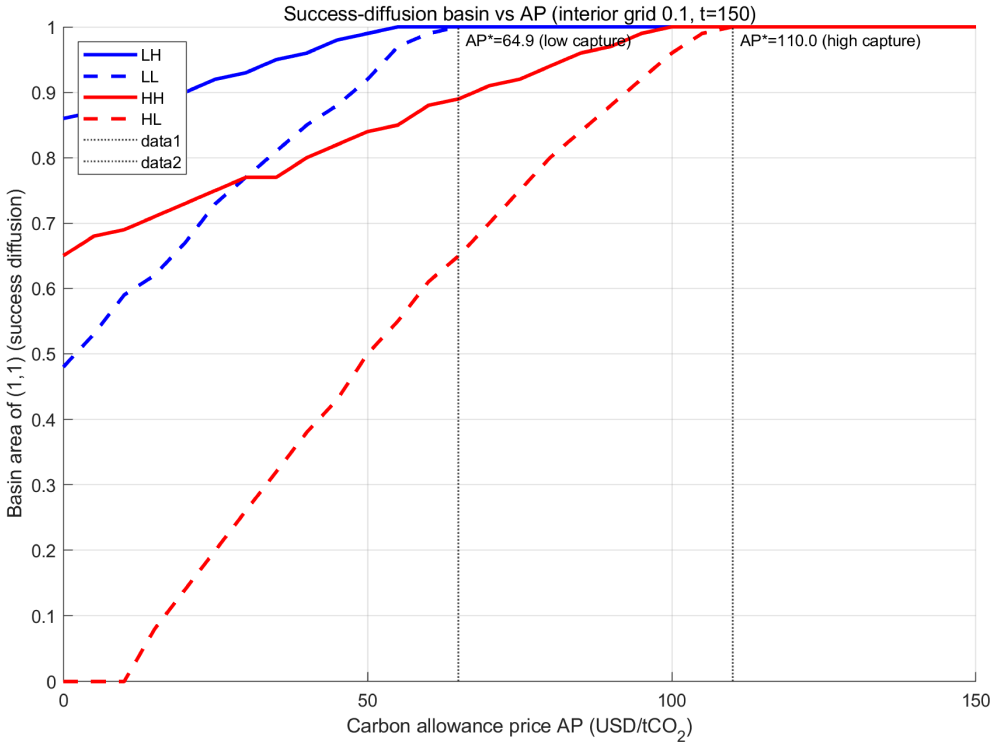


Figure 6. Estimated basin-of-attraction share of the successful diffusion equilibrium (1,1) as a function of carbon allowance price.

Table 5. Carbon allowance price levels for threshold-centered sensitivity analysis.

Relative Price Level	Low-Capture-Cost Scenario	High-Capture-Cost Scenario
0.90T	58.4	99.0
0.95T	61.7	104.5
0.99T	64.3	108.9
T	64.9	110.0
1.01T	65.5	111.1
1.05T	68.1	115.5
1.10T	71.4	121.0

Overall, the analytical threshold is determined by capture costs, whereas other techno-economic parameters can influence the evolutionary path and the set of initial conditions from which successful technology diffusion is reached. The distinction between the critical price and the basin of attraction is important: the former identifies a stability boundary under the model, while the latter describes outcomes over the sampled initial states.

4.4. Robustness Analysis

This subsection examines their robustness in two respects: the dependence of the successful-diffusion outcome on initial adoption shares, and the stability of the equilibrium under stochastic allowance-price volatility.

To assess the dependence of the diffusion outcome on initial adoption shares, the basin of attraction of the successful-diffusion equilibrium (1,1) is computed as the fraction of sampled interior initial states (x0, y0) that converge to (1,1) under the replicator dynamics over a sufficiently long horizon (t = 150). The initial states are sampled on a grid with step 0.05 over $\{0.05, 0.15, \ldots, 0.95\}^2$ (19 × 19 interior points), and a trajectory is counted as

converged when both adoption ratios exceed 0.98 at t = 150; the basin area is then the share of sampled initial states satisfying this criterion. As shown in Figure 7, this basin area is plotted against the allowance price AP for the LH and HL scenarios. The vertical dashed lines mark the analytical thresholds AP* = 64.9 and 110.0 USD/tCO_2, derived from the equilibrium stability analysis of the deterministic replicator dynamics. These theoretical thresholds differ from the numerical prices at which the sampled basin fraction reaches unity. In the HL scenario, the basin fraction reaches unity at approximately AP = 102.5 USD/tCO_2, before the analytical threshold of 110.0 USD/tCO_2. In the LH scenario, the high enhanced-oil-recovery revenue already gives (1,1) a large attraction region (≈0.89 at AP = 0), and the basin fraction reaches unity at approximately AP = 50 USD/tCO_2, before the analytical threshold of 64.9 USD/tCO_2. These numerical transition points reflect the finite initial-state grid and simulation horizon and should not be interpreted as estimates of the analytical thresholds. At and above the analytical thresholds, all sampled initial states converge to (1,1), indicating reduced dependence on initial adoption shares.

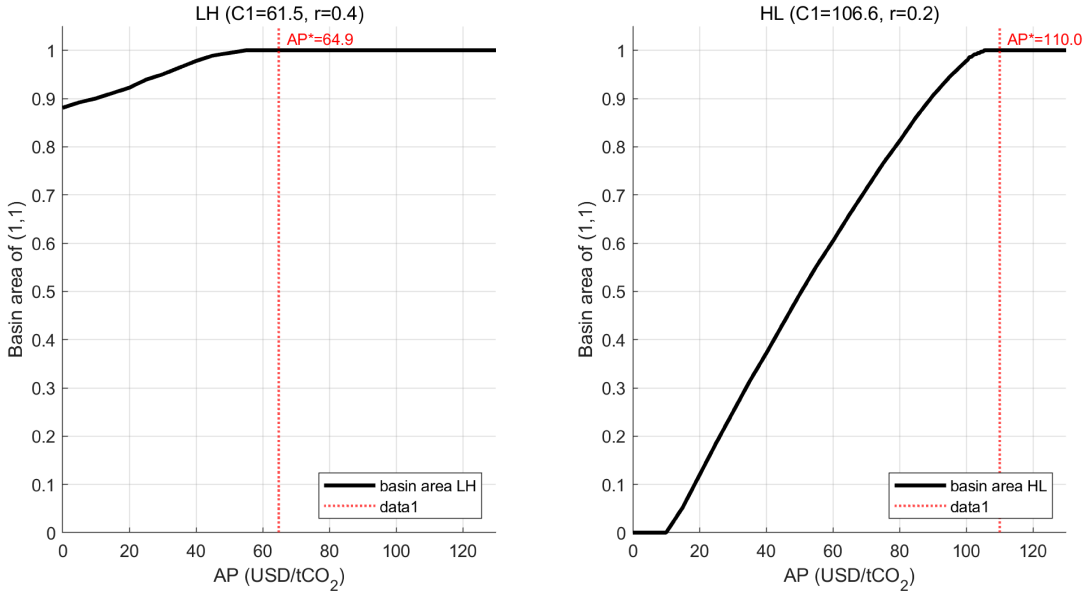


Figure 7. Basin of attraction of the successful-diffusion equilibrium (1,1) versus AP for the LH and HL scenarios; vertical lines mark the analytical thresholds (64.9 and 110.0 USD/tCO_2).

The robustness of these results to allowance-price volatility is examined by augmenting the replicator dynamics with a mean-reverting Ornstein–Uhlenbeck (OU) shock to the allowance price $dAP = \kappa\left(\overline{AP} - AP\right)dt + \sigma\, dW$, with reversion rate $\kappa = 0.5$ and noise intensity $\sigma \in 0$ and 6 USD/tCO_2 (the representative paths in Figure 8 are computed with $\sigma = 6$). The OU process is initialized at its long-run mean $\overline{AP}$ and fluctuates around it; no explicit lower-bound clamp is applied to the sampled allowance price, but the strong mean reversion keeps the probability of negative excursions negligible within the simulation horizon.

The OU path is discretized with the Euler–Maruyama scheme, $AP_{k+1} = AP_k + \kappa\left(\overline{AP} - AP_k\right)\Delta t + \sigma\sqrt{\Delta t}\,\varepsilon_k$, with $\Delta t = 0.02$, horizon T = 100 and the innovations $\varepsilon(k)$ drawn independently from the standard normal distribution N(0,1) using the seeded generator rng (20261020); the Monte Carlo trial count is N = 40 for the representative paths in Figure 8, and all simulations start from the same initial adoption shares $(x0, y0) = (0.15, 0.15)$. At each time step the sampled allowance price enters the bargaining formula to recompute the transaction price P, which in turn drives the two replicator equations; both equations are advanced synchronously with the same explicit Euler step and the state variables are clamped to the unit square. Since CCS-EOR diffusion requires the joint participation of both types of

enterprises, successful diffusion is defined by both adoption ratios exceeding 0.98. As shown in Figure 8, representative adoption paths of the utilization (x) and capture (y) enterprises are presented for long-run mean allowance prices $\overline{AP}$ = 60, 64.9 and 80 USD/tCO$_2$ in the LH scenario. To display convergence clearly, only the interval $t \in [0, 30]$ is shown in Figure 8, although the full simulations run to T = 100; beyond this window, both x and y remain at unity. The plotted stochastic mean is the ensemble average over the N = 40 trials at each time point. In each panel, both x and y rise from the initial share and converge to 1 under both the deterministic dynamics and the stochastic mean, with bounded fluctuations; these results suggest that coordinated adoption remains relatively stable under the examined stochastic conditions.

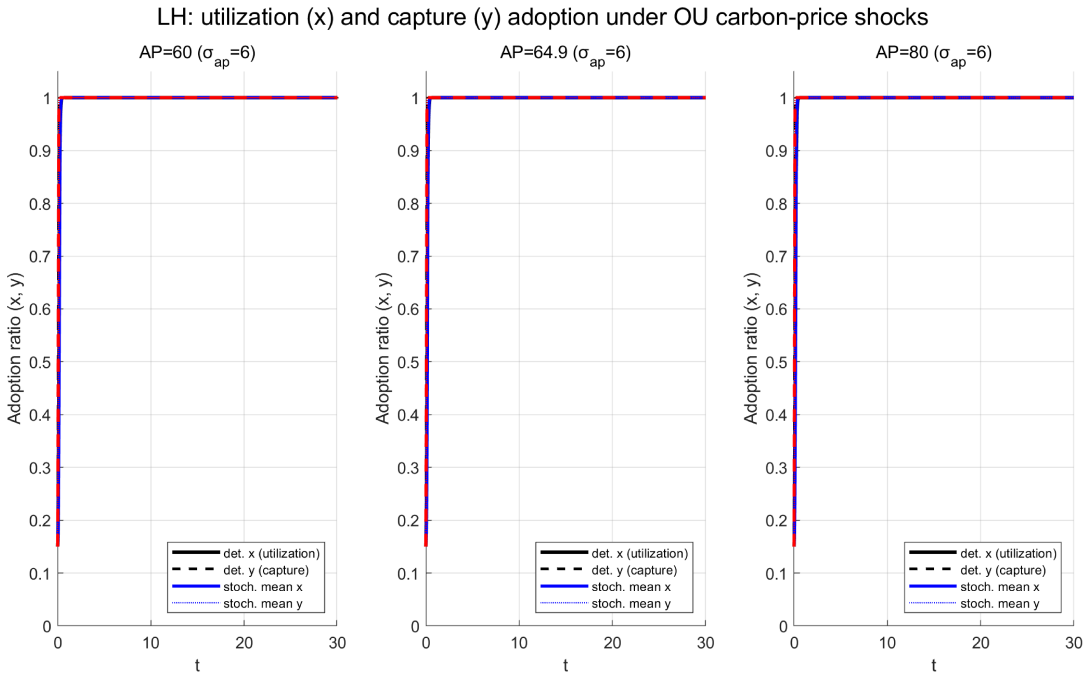


Figure 8. Adoption paths of utilization (x) and capture (y) enterprises under OU allowance-price shocks for long-run mean prices AP = 60, 64.9 and 80 USD/tCO$_2$ in the LH scenario. Full simulations run to T = 100; only $t \in [0, 30]$ is shown to illustrate convergence.

These results indicate that higher carbon allowance prices expand the basin of attraction of successful CCS-EOR technology diffusion, reducing the dependence of diffusion outcomes on initial adoption conditions. Furthermore, the adoption dynamics remain relatively stable under the stochastic carbon allowance price fluctuations examined, providing additional support for the robustness of the technology diffusion outcomes.

5. Conclusions and Recommendations

5.1. Conclusions

In summary, this study draws the following conclusions:

(1) Carbon allowance constraints exert a qualitative driving effect on CCS-EOR technology diffusion at the institutional level, while carbon allowance prices demonstrate a quantitative moderating effect. For CCS-EOR technology diffusion, the existence of carbon allowance constraints provides significant qualitative promotion, with their regulatory rigidity establishing the fundamental policy conditions for low-carbon technology adoption. However, parameter adjustments to constraint intensity show insignificant impacts. In contrast, carbon price fluctuations significantly influence CCS-EOR technology diffusion: higher carbon prices yield more pronounced promotional effects.

(2) The impact of carbon markets on utilization enterprises is indirect, mediated through the CO_2 transaction price between capture and utilization enterprises. Driven by carbon markets, techno-economic parameters influence CCS-EOR technology diffusion through multiple pathways: capture costs directly determine the upper carbon price threshold; oil displacement benefits, capture costs, transportation costs, and EOR costs collectively determine the lower threshold. The CO_2 transaction price serves as the channel through which carbon markets indirectly affect the adoption willingness of utilization enterprises.

(3) Under scenarios of low and high capture costs, the carbon price thresholds are 64.9 and 110.0 USD/tCO_2, respectively. Across the four representative techno-economic scenarios, the carbon price thresholds exhibit differentiated constraints: for low capture cost–high oil displacement benefit, low capture cost–low oil displacement benefit, high capture cost–high oil displacement benefit, and high capture cost–low oil displacement benefit scenarios, the thresholds are 64.9, 64.9, 110.0, and 110.0 USD/tCO_2, respectively. When the carbon allowance prices exceed 64.9, 64.9, 110.0, and 110.0 USD/tCO_2, respectively, in these four scenarios, CCS-EOR technology diffusion occurs without external conditions. If the prices fall below these thresholds, technology diffusion depends on critical initial adoption willingness, with lower carbon prices demanding more stringent initial adoption probability requirements.

5.2. Recommendations

Based on the findings, this study proposes the following recommendations:

(1) Strengthen carbon market mechanisms and advance carbon price rationalization reforms. Current carbon market development suffers from institutional shortcomings, including limited sectoral coverage, severe regional market fragmentation, and distorted carbon price signals, resulting in persistent deviations from environmental damage cost benchmarks. Legislative measures should expand the carbon market coverage by incorporating high-emission sectors (e.g., iron, steel, building materials) into mandatory emission reduction systems and establishing cross-regional linkage trading mechanisms. Concurrently, refining the carbon pricing formation mechanisms can ensure that carbon prices fully reflect the marginal abatement costs. Enhancing the clarity and stability of carbon price signals will provide predictable market conditions for CCS-EOR investment decisions.

(2) Accelerate CCS-EOR technology advancement to reduce capture costs and implement targeted carbon capture subsidies. High capture costs remain the primary barrier to CCS-EOR technology diffusion. Immediate actions include establishing dedicated R&D subsidies for carbon capture technologies to drive innovation and cost reduction. Complementary carbon capture subsidy policies should directly support capture enterprises and effectively lower their operational costs. This approach will significantly reduce the carbon price dependency threshold for technology diffusion.

(3) Develop a demonstration-led technology promotion framework to amplify low-carbon technology spillover effects. During the transition phase of incomplete carbon pricing mechanisms, technology diffusion remains contingent on critical initial adoption probabilities. Establishing national CCS-EOR demonstration project clusters spanning diverse geological conditions and technical pathways will create full-scenario technology validation platforms. Government-led demonstrations can mitigate the adoption risks of the private sector. Expanding the promotion of CCS-EOR demonstration projects will elevate initial adoption probabilities.

Author Contributions: Conceptualization, J.Z., C.L. and Y.L.; Methodology, J.Z. and C.L.; Software, C.L.; Validation, J.Z., Y.L. and Y.J.; Formal Analysis, J.Z. and C.L.; Data Curation, J.Z. and C.L.; Writing—Original Draft Preparation, J.Z. and C.L.; Writing—Review and Editing, J.Z.; Visualization,

J.Z. and C.L.; Supervision, Y.L. and Y.J.; Project Administration, Y.L. and Y.J.; Funding Acquisition, J.Z., Y.L. and Y.J. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the China Postdoctoral Science Foundation (Grant No. 2025M783721), the Major National Social Science Projects (Grant No. 24VHQ005), and the National Natural Science Foundation of China (Grant No. 72574205).

Data Availability Statement: The original contributions presented in this study are included in the article. Further inquiries can be directed to the corresponding author.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

CCS	Carbon Capture and Storage
CCUS	Carbon Capture, Utilization, and Storage
EOR	Enhanced Oil Recovery
CCS-EOR	Carbon Capture and Storage with Enhanced Oil Recovery
ESS	Evolutionarily Stable Strategy
OU	Ornstein–Uhlenbeck
LH	Low Capture Cost–High Oil Displacement Benefit
LL	Low Capture Cost–Low Oil Displacement Benefit
HH	High Capture Cost–High Oil Displacement Benefit
HL	High Capture Cost–Low Oil Displacement Benefit

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