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Getting ready for future carbon abatement under uncertainty – Key factors driving investment with policy implications

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ABSTRACT

Carbon capture and storage (CCS) is considered a key technology option for abating CO_2 emissions in carbon-intensive sectors, e.g. the power sector. However, high investment costs and risk hinder the diffusion of CCS. To avoid stranded assets or high future costs for retrofitting, new plants can be made carbon capture ready (CCR) to enable them to accommodate future CCS retrofitting at low additional costs. Current CCR investment decisions are closely related to future CCS retrofitting and CCS operation decisions in subsequent stages, all of which would be affected by uncertainties. We develop a three-stage CCR investment decision model under multiple uncertainties which allows for investment and especially operating flexibilities. Applying this model to China shows that CCS operating flexibility under the carbon-pricing scheme may actually lower the probability of investing in a CCR plant, and neglecting it may overestimate the propensity for investing in CCR. Moreover, learning effects, which reduce the costs of future CCS retrofitting, may be detrimental to CCR investment, indicating that the policy support for research on, development of, and deployment of CCS to reduce CCS costs should be coordinated with CCR investments. Although higher electricity prices can increase the value of an investment opportunity, it may restrain CCR investment. Finally, CCR investment does not appear to be economically viable under current conditions in China because of low carbon prices, high carbon price risks, high CCR investment costs and the high opportunity costs of CCS operation.

1. Introduction

To reduce the risks and catastrophic effects of climate change, 195 countries signed the Paris Agreement in December 2015. In this first-ever legally binding global climate deal governments agreed to the long-term goal of keeping global average temperature increase well below 2 °C above pre-industrial levels while aiming to limit the increase to 1.5 °C. The power sector is responsible for >40% of total global energy-related CO_2 emissions and needs to be decarbonized to realize the climate target (IEA, 2013a). While in several countries new sources of energy have started to gradually change the energy landscape, about two-thirds of global electricity is still produced from the fossil fuels coal (41.3%), natural gas (21.7%), and oil (4.4%) (IEA, 2015a).

While large European countries such as Germany, France and the UK tend to focus on renewable and nuclear energy sources, carbon capture and storage (CCS) is considered a key technology in the effort to realize large-scale CO_2 emission abatement, especially in emerging economies such as China and India (IEA, 2010a). So far though, plant operators have been slow to invest in CCS because the related costs and risks involved are high (IEA, 2013b). More specifically, adding CCS to any process increases capital costs, requiring additional expenditure for CO_2 capture and compression equipment or for CO_2 transportation and storage. CCS also incurs higher operating costs since energy is required to separate the CO_2 from the exhaust streams, resulting in about a 10% loss in power plant efficiency (Sekar, 2005; Abadie and Chamorro, 2008; Rohlfs and Madlener, 2011). Thus, CCS is profitable only if carbon costs are sufficiently high, e.g., because a carbon tax or an emissions

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trading system (ETS) is in place.[1] The investment risks that accompany a CCS installation include uncertainty about future prices (of fuel, electricity, and CO_2 certificates), technology performance, investment costs, regulation, and acceptance of CCS by civil society (IEA, 2007a). These potential disadvantages increase the likelihood that new fossil fuel power plants will be built without a CO_2 abatement option.

To avoid the risk of stranded assets or the high costs of retrofitting should future market or regulatory conditions change,[2] new fossil fuel plants can be made carbon capture ready (CCR) so they can easily accommodate future carbon capture equipment. Thus, CCR provides the investor with the option of retrofitting a plant with CCS in the future at lower costs than those he would have to incur if he had invested in a conventional plant (a Non-CCR plant). A CCR plant, however, incurs higher initial investment costs than a Non-CCR plant (IEA, 2007b). In addition, when deciding among competing projects investors also need to take into account future CCS retrofitting and operating decisions. In particular, even if a CCS retrofit were to be implemented, market conditions may later turn out to favor running the plant in CCS-off mode (to avoid the efficiency loss) and to acquire the desired number of certificates on the CO_2-certificates market instead (Mo and Zhu, 2014). Furthermore, high capital expenditure and the irreversibility of a CCS retrofit investment may lead investors to delay CCS retrofitting until market and regulatory conditions improve (McDonald and Siegel, 1986; Abadie and Chamorro, 2008).

In summary, to make correct power plant investment decisions operators must navigate through three stages of decision-making: (i) the initial decision between investing in a CCR plant or a Non-CCR plant; (ii) the decision whether and when to implement a CCS retrofit, and (iii) the decision whether to operate in CCS mode. Finally, a plant manager has the option of permanently shutting down a plant during the period corresponding to each stage if the manager expects that continuing to operate the plant will be a losing proposition. Clearly, decisions at each stage will be affected by investment and operating decisions made in the preceding stages. As a consequence, the CCR investment decision is a multi-stage decision problem under high risk.

So far only a few studies have focused on CCR investment. Bohm et al. (2007) summarizes the CCR investment options for pulverized coal (PC) plants and integrated gasification and combined cycle (IGCC) plants, and estimate the net present value (NPV) of plants for a range of CCR pre-investment levels. Because many uncertainties affect the profitability of a CCR investment, several studies involved probabilistic analyses of CCR investment. For example, Rochedo and Szklo (2013) assessed the profitability of investing in CCR for coal-based power plants, varying the timing of CCS retrofitting. Their findings showed that pre-investments in CCR are profitable only when the retrofitting of CCS occurs in the near future. However, the framework employed by Rochedo and Szklo (2013) did not allow for flexibility in CCR investments or operations. As management flexibility may play an important role in investment decision-making under uncertainty (Fleten and Näsäkkälä, 2010; Heydari et al., 2012), Liang et al. (2009) assessed the value of CCR in newly built PC-fired power plants, allowing for timing flexibility of the CCS retrofit. Their findings indicate that the value of CCR is significantly understated without sufficient timing flexibility. Based on a multi-factor real options model, Rohlfs and Madlener (2011, 2013) evaluated CCR investment in a coal plant. They found that CCR investment turned out to be profitable only under very specific conditions, such as a high and stable carbon price, and the CCR plant option is typically dominated by other technology options.

While Liang et al. (2009) and Rohlfs and Madlener (2011, 2013) allow for flexibility in the timing of CCS retrofitting, they do not consider CCS operating flexibility. Likewise, no study has yet considered the effects of interaction between the various investment and operating flexibilities on the CCR investment decision. In addition, the CCR investment decision is driven mostly by relevant policy, e.g. carbon pricing policy, research and development (R&D) policy, and energy pricing policy. However, the effect of any such policy may be vague and even detrimental to CCR investment, as a result of the complexity of the investment decision, and it should be evaluated cautiously to avoid possible policy failure or conflicts. The extant literature has not explored in depth the impact of relevant policy on the decision to invest in CCR.

In this paper we first develop a CCR investment decision model using the dynamic programming method, which captures the investment and operational flexibilities in the three decision stages and allows for multiple uncertainties. Then we parameterize the model for a newly built supercritical pulverized coal plant in China, as China is the world's largest emitter of greenhouse gases, and the power sector contributes about 50% of total energy-related CO_2 emissions (IEA, 2015b). We then use Monte Carlo simulation methods to accommodate the complexity of the decision model and least-square methods (LSM) to improve the accuracy of the solution. Based on this model, we explore the impact of CCR investment on CCS retrofitting and CO_2 abatement, of operating flexibility on CCR investment and, in particular, of key policy factors, e.g. carbon pricing, electricity pricing, and learning effect of CCS driven by R&D, on investment in CCR.

Thus, we contribute to the extant literature by building a novel CCR investment decision model under multiple uncertainties involving a three-stage decision process and various decision flexibilities. In particular, allowing for CCS operating flexibility more adequately reflects actual plant operating conditions (Chalmers et al., 2009). While these features increase the complexity of the analysis compared with previous approaches, they also allow for novel, arguably surprising, insights. For example, we show that operating flexibility may lower the probability that an operator will invest in CCR under the carbon pricing policy. Thus, analyses neglecting CCS operating flexibility may overestimate the propensity for investing in a CCR plant. Furthermore, we show that learning effects, which bring down the costs of CCS retrofitting, may be detrimental to CCR investment. Finally, we found that higher electricity prices lower the probability that a given operator will invest in a CCR plant. The novel results referred to above may have significant policy implications in practice.

The structure of the paper is as follows: Section 2 describes the CCR investment decision model in detail. Section 3 presents the key parameters of the case study, and Section 4 presents the main simulation results. Section 5 discusses the main findings and concludes.

2. Modeling CCR investment under uncertainty

This section presents our novel three-stage CCR investment decision model. First, in Section 2.1 we model uncertainties affecting CCR investment in China. Then in Section 2.2 we present the decision process related to CCR investment. Section 2.3 introduces our approach to solving the model.

2.1. Modeling uncertainties

Investors in CCR for new power plants face uncertain future costs and revenues, because electricity prices, fuel prices, and carbon prices are uncertain. We assume that these prices follow stochastic processes. In general, electricity prices show short-run and a long-run dynamics (Schwartz and Smith, 2000; Abadie and Chamorro, 2008). Short-run behavior displays mean reversion, seasonality, and stochastic volatility,

[1] Unlike under a carbon tax, the carbon costs involved in an ETS are volatile since the price of the CO_2 certificates is endogenously determined by supply and demand. Companies with high CO_2 abatement costs may find it more profitable to purchase these certificates than to install abatement technology. For example, the EU ETS has been in place since 2005 and is considered the key EU climate policy instrument for reducing carbon emissions cost-efficiently. Since 2013 China has been experimenting with ETSs in seven regions. These pilot schemes are scheduled to be replaced by a national ETS in 2017. In this paper we assume that an ETS is in place. Carbon prices then refer to the prices of CO_2 certificates.

[2] "Stranded assets" here means that companies risk investing in plants with long lifetimes of typically 40 years or more (IEA, 2007b) that—unless they can be retrofitted with CCS technology—will later be banned by law or become too expensive to operate because of more stringent emission regulations.

while long-term behavior is determined by equilibrium price dynamics. In liberalized electricity markets, the short-run characteristics affect plant operation, as prices may vary significantly. In China, however, the electricity market is still regulated, and the benchmark electricity prices are determined by the National Development and Reform Commission (NDRC). In fact, electricity prices in China are typically adjusted once a year only and sometimes remain unchanged even for longer periods of time. Therefore, the short-run behavior of electricity prices has little effect on plant operations in China, which are instead driven by long-run dynamics. In addition, current on-grid electricity prices in China are generally considered low (OVO Energy, 2015; Statista, 2015), but they are expected to increase in the wake of future market-oriented reforms (Zhou et al., 2010; Zhu and Fan, 2011; Mo et al., 2016). Following the literature (e.g. i.e. Zhou et al., 2010; Rohlfs and Madlener, 2011; Zhu and Fan, 2011; Mo et al., 2016) we therefore employ a geometric Brownian motion (GBM) process to model the long-run trend for and volatility of electricity prices in China.[3]

The evolution of coal prices seems to be mean-reverting over a very long period of time, although the reversion is slow and often takes as long as a decade. According to Pindyck (1999) mean reversion in the coal market takes about ten years. However, current coal prices in China are low, mainly because of excess coal production capacity in the past. Since the Chinese government has started to implement measures to reduce excess capacity, the coal supply is expected to shrink and coal prices are expected to rise in the mid to long term. Exploring the implications of energy price model choice for investment decisions, the empirical results reported by Pindyck (1999) further suggest that employing a GBM process is unlikely to lead to large errors in irreversible investment decisions for which energy prices are key stochastic variables. Like Siddiqui et al. (2007), Kumbaroğlu et al. (2008), Fuss et al. (2008), and Liang et al. (2009), we model coal price evolution as a GBM.

Current carbon prices are relatively low but are expected to increase gradually with the carbon budget becoming more stringent in the mid- and long-term future, reflecting the world's commitment to take on more ambitious carbon emission reduction targets over time. Meanwhile the evolution of carbon prices is subject to many uncertain factors, reflecting uncertainty in both supply and demand factors that affect prices. We therefore model future carbon prices also as a GBM process.

More specifically, Eq. (1) describes the evolution of the various prices as follows:

$$dP_{i-t} = \alpha_i P_{i-t} dt + \sigma_i P_{i-t} dW_{i-t} \tag{1}$$

where $i = 1, 2, 3$, and P_{1-t}, P_{2-t} and P_{3-t} represent the coal price, the electricity price, and the carbon price, respectively; α_i stands for the price drift rate; σ_i is the instantaneous price volatility; and dW_{i-t} is the increment to a standard Wiener process, which is assumed to be normally distributed with a mean of zero and a variance of dt.

Further, the risk-neutral form of the process is as follows

$$dP_{i-t} = (\alpha_i - \lambda_i) P_{i-t} dt + \sigma_i P_{i-t} dW_{i-t} \tag{2}$$

where λ_i is the risk premium, and $(\alpha_i - \lambda_i)$ is the risk-adjusted drift rate (Dixit and Pindyck, 1994).

Let $X_{i-t} = \ln(P_{i-t})$; applying Ito's Lemma yields

$$dX_{i-t} = \left(\alpha_i - {}^1/_2\sigma_i^2 - \lambda_i\right) dt + \sigma_i dW_{i-t} \tag{3}$$

[3] In comparison, electricity price dynamics for liberalized electricity markets have been modeled as a mean-reverting process (e.g. Abadie and Chamorro, 2008). As a drawback, simulations using a GBM may generate some paths with extremely high electricity prices. However, since the probability of extremely high electricity prices is low, the main simulation results for the CCR investment decision as presented in Section 4 will not change.

In the numerical study we use a discrete approximation as follows to simulate the price evolution:

$$P_{i-(t+1)} = P_{i-t} \exp\left[\left(\alpha_i - {}^1/_2\sigma_i^2 - \lambda_i\right)\Delta t + \sigma_i (\Delta t)^{1/2} \varepsilon_t\right] \tag{4}$$

In addition, to allow electricity, coal, and carbon prices to be correlated, we add the following conditions (Dixit and Pindyck, 1994):

$$\begin{cases} dW_{1-t} dW_{2-t} = \rho_{1-2} dt, \\ dW_{1-t} dW_{3-t} = \rho_{1-3} dt, \\ dW_{2-t} dW_{3-t} = \rho_{2-3} dt. \end{cases} \tag{5}$$

where ρ_{1-2}, ρ_{1-3} and ρ_{2-3} are the coefficients of correlation, which reflect the extent to which both series move together beyond their trends.

2.2. Modeling CCR investment decision

The lifetime of a power plant lasts from period 0 to period T, and can be divided into three stages (see Fig. 1)[4]: period 0 to period T_2 (Stage 1), period $T_2 + 1$ to period T_r (Stage 2) and period $T_r + 1$ until the end of the lifetime of the power plant in period T (Stage 3). In the first stage, at the beginning of the decision process an investor decides what type of plant to build, a conventional Non-CCR plant or a CCR plant. The construction of the plant will be finished at T_1, and it is assumed that a carbon pricing system is introduced at T_2.[5] Between T_1 and T_2, the investor may decommission the plant in advance if he anticipates that keeping the plant running would reduce total profits. In the second stage, from $T_2 + 1$ on, the investor first decides in each period whether to decommission the power plant; if he chooses to continue operating the plant, then he must decide whether to retrofit the plant with CCS immediately or delay the retrofit. T_r denotes the period of retrofitting ($T_2 \leq T_r \leq T$), which should be decided by optimization. In the third stage, i.e., from $T_r + N$ to T,[6] in each period the investor again first decides whether to decommission the plant in advance, and then decides whether to run the plant in CCS-mode to abate CO_2 emission or to suspend CCS operation temporarily depending on market conditions if continuing operating the plant is adopted. Thus, the CCR investment decision is affected by the CCS retrofit decision in Stage 2 and by the CCS operation decision in Stage 3. We therefore employ dynamic programming methods and begin the formal presentation of our model with the final stage.

2.2.1. Stage 3: from period $T_r + N$ to period T

From $T_r + N$ on, the investor may—as in previous stages—decide whether to decommission the plant in advance in any period. He may then decide whether to operate the plant in CCS mode or not.

We assume that the investor wants to maximize net cash flow in each period. The decision problem for each period in Stage 3 then becomes:

$$\begin{cases} Abate\ CO_2\ \ emission, \ \ if\ CF_t^{SCC} < CF_t^{CC} \\ Suspend\ CO_2\ abatement, if\ CF_t^{SCC} \geq CF_t^{CC} \end{cases} \tag{6}$$

[4] In the case study, one period corresponds to one-quarter of a year.

[5] In our case study we assume that plant construction will take two years, i.e. eight periods. In addition, we assume that the carbon pricing policy is introduced after the plant construction is finished at T_2. However, if it was already in place when the investment decision was made, there would be no decision about whether to decommission the plant in Stage 1. In this case, after finishing power plant construction at T_1, the investor would face the decision described in Stage 2.

[6] It is assumed that it takes N periods to retrofit the plant with CCS. In the case study, the CCS retrofit takes one year, so N = 4.

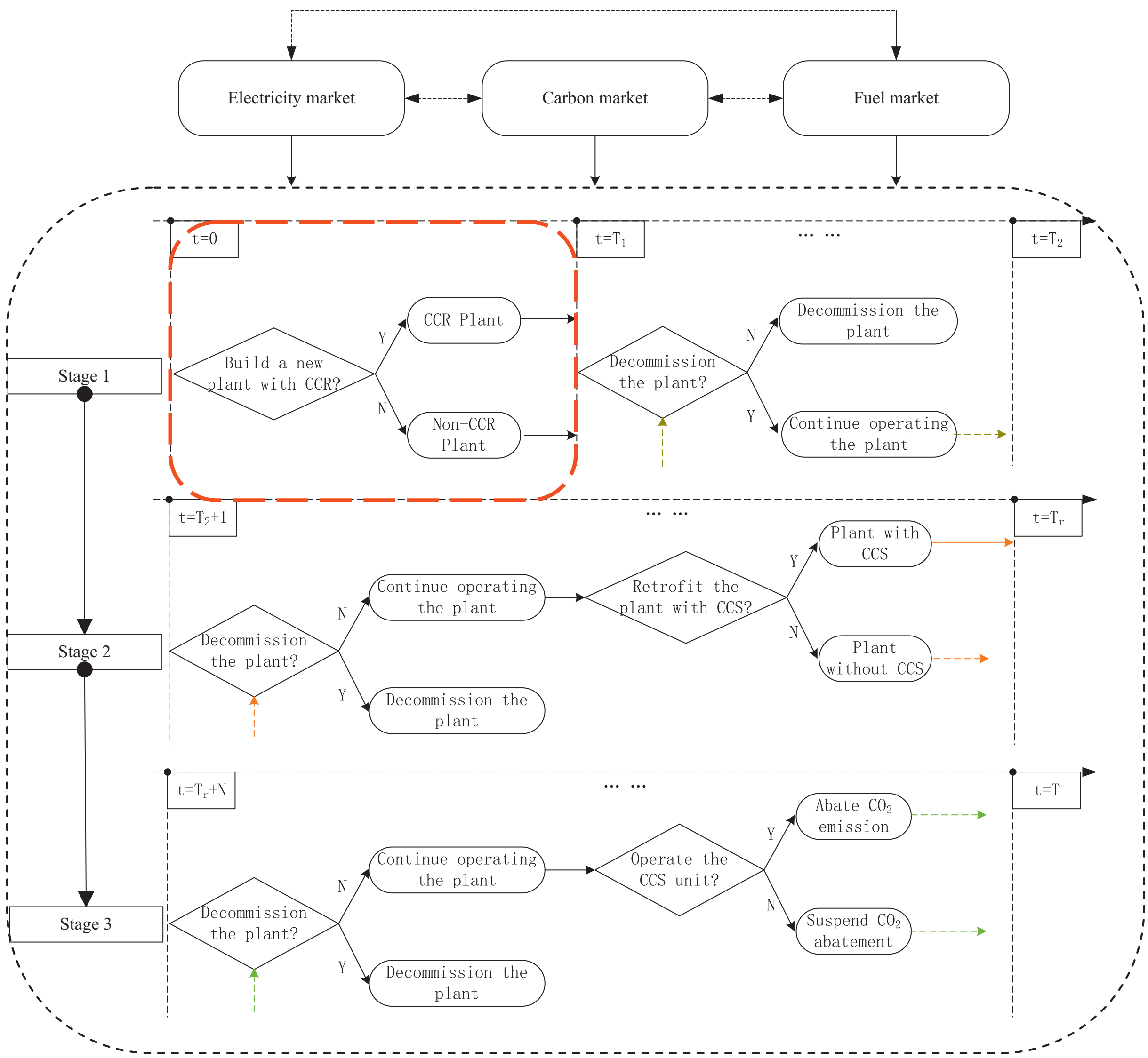

Fig. 1. The decision process involved in CCR investment in new power plant.

where CF_t^{CC} and CF_t^{SCC} are the cash flows when operating in CCS mode and CCS-off mode, respectively, in period t.[7]

The optimized cash flow is then[8]

$$CF_t = MAX\left(CF_t^{SCC}, CF_t^{CC}\right) \tag{7}$$

The investor will close the plant in period t if the expected economic value from continuing to operate the plant V_t^3 is less than the NPV from decommissioning the plant: NPV_t^A.[9]

$$\begin{cases} \text{Decommission the plant, if } E_t\left(V_t^3\right) \le NPV_t^A \\ \text{Continue operating the the plant, if } E_t\left(V_t^3\right) > NPV_t^A \end{cases} \quad (T_r + N \le t \le T) \tag{8}$$

V_t^3 can be expressed as

$$V_t^3 = CF_t + e^{-r\Delta t}\, MAX\left(NPV_{t+\Delta t}^A, E_t\left(V_{t+\Delta t}^3\right)\right) \tag{9}$$

where r is the discount rate and Δt is the time step of each period.

The optimized economic value in period t is

$$F_t^3 = MAX\left(NPV_t^A, E\left(V_t^3\right)\right) \tag{10}$$

Eq. (10) then becomes the basis for the decision whether to retrofit the plant with CCS in Stage 2. The boundary condition of V_t^3 in the final period T is

$$V_T^3 = CF_T \tag{11}$$

The boundary condition (11) allows V_t^3 and F_t^3 to be solved backwards.

[7] See the details on the calculation of the net cash flow in each period CF_t^{CC} and CF_t^{SCC} in Appendix A.

[8] The optimal cash flow can be zero if the greater of the cash flows from CCS mode and CCS-off mode is zero.

[9] For simplicity we assume that decommissioning the plant yields a net cash flow of 0.

2.2.2. Stage 2: from period $T_2 + 1$ to period Tr

Unless the investor decommissions the plant, he decides whether to immediately retrofit the plant with CCS or to delay the retrofit. In the latter case, the investor has to pay for all CO_2 emissions in that period. If he invests in CCS in period t (from $T_2 + 1$ to T_r), the total NPV is

$$NPV_t = e^{-rN\Delta t} F^3_{t+N} - C_t^{CCS-outlay} \tag{12}$$

where $C_t^{CCS-outlay}$ is the investment cost of a CCS retrofit in period t and F^3_{t+N} is the expected NPV of the future net cash flow from period t + N to period T after retrofitting the power plant (i.e., Eq. (10)).

If the investor delays the retrofit, the economic value of the investment opportunity becomes

$$V_t^2 = CF_t^{BR} + e^{-r\Delta t} MAX\left(NPV_{t+\Delta t}, E_t\left(V^2_{t+\Delta t}\right)\right) \tag{13}$$

where CF_t^{BR} is the cash flow before a CCS retrofit in period t and after the government introduced the carbon pricing system in T_2.[10]

The CCS retrofit investment in Stage 2 is then governed by the following decision rule for each t:

$$\begin{cases} \text{Retrofit plant with CCS immediately}, \text{if } E_t(NPV_t) > E_t\left(V_t^2\right), \\ \text{Delay the CCS retrofit}, \text{if } E_t(NPV_t) \le E_t\left(V_t^2\right). \end{cases} \tag{14}$$

The optimized economic value from continuing to operate the plant in period t is

$$f_t^2 = MAX\left(E_t(NPV_t), E_t\left(V_t^2\right)\right) \tag{15}$$

The decision rules for deciding whether to decommission the plant become

$$\begin{cases} \text{Decommission the plant}, & \text{if } f_t^2 \le NPV_t^A \\ \text{Continue operating the plant}, & \text{if } f_t^2 > NPV_t^A \end{cases} \tag{16}$$

Then, the optimized economic value in period t in the second stage is

$$F_t^2 = MAX\left(f_t^2, NPV_t^A\right) \tag{17}$$

Eq. (17) allows us to derive the optimized economic value at time $(T_2 + \Delta t)$, ${F_{T_2+\Delta t}}^2$, which the investor takes into account when making a decision in Stage 1.

At time T, the investor has no incentive to invest in a CCS retrofit, because there is no time left to recover the investment costs. Then, the total expected NPV from delaying the CCS investment at time T V_T^2 is (boundary condition)

$$V_T^2 = MAX\left(0, CF_T^{BR}\right) \tag{18}$$

where CF_T^{BR} is the cash flow in period T before the CCS retrofit. Eq. (18) allows us to solve for V_t^2, f_t^2 and F_t^2 backwards.

2.2.3. Stage 1: from period 0 to period T_2

We can divide this stage into two parts arranged in chronological order. At the beginning of the plant investment decision period T_0, the investor first decides what type of plant to build—a traditional Non-CCR plant or a CCR plant. After the plant construction is finished in period T_1, he has the option of decommissioning the plant in advance until T_2 when carbon pricing is introduced. Also, we describe the decision process in reverse order.

In period t ($T_1 \le t \le T_2$), continuing operating the plant yields the NPV V_t^1

$$V_t^1 = CF_t^{BETS} + e^{-r\Delta t} MAX\left(NPV^A_{t+\Delta t}, E_t\left(V^1_{t+\Delta t}\right)\right) \tag{19}$$

where CF_t^{BETS} is the cash flow in period t before carbon pricing is introduced.[11] Note that in each period of this stage there is no regulation of CO_2 emissions. The decision whether to decommission the plant after the plant has been built before T_2 when carbon pricing is introduced is as follows:

$$\begin{cases} \text{Decommission the plant}, \ \text{if } E_t\left(V_t^1\right) \le NPV_t^A \\ \text{Continue operating the plant}, \ \text{if } E_t\left(V_t^1\right) > NPV_t^A \end{cases} \tag{20}$$

The optimized economic value in each period t is

$$F_t^1 = MAX\left(E_t\left(V_t^1\right), NPV_t^A\right) \tag{21}$$

Based on Eq. (21), we can derive the optimized economic value at time T_1, ${F_{T_1}}^1$.

The boundary condition in period T_2 is then

$$V^1_{T_2} = CF^{BETS}_{T_2} + e^{-r\Delta t} F^2_{T_2+\Delta t} \tag{22}$$

where ${F_{T_2+\Delta t}}^2$ is obtained from Stage 2 (Eq. (17)). In period T_0, the investor decides what type of plant to build. The economic values of the CCR plant (${S_{T_0}}^{CCR}$) and Non-CCR plant (${S_{T_0}}^{NCCR}$) are as follows:

$$S^{CCR}_{T_0} = -C^{CCR}_{T_0} + e^{-r(T_1-T_0)} F^{1-CCR}_{T_1} \tag{23}$$

$$S^{NCCR}_{T_0} = -C^{NCCR}_{T_0} + e^{-r(T_1-T_0)} F^{1-NCCR}_{T_1} \tag{24}$$

where ${C_{T_0}}^{CCR}$ and ${C_{T_0}}^{NCCR}$ are the investment costs of the CCR plant and the Non-CCR plant, respectively, and ${F_{T_1}}^{1-CCR}$ and ${F_{T_1}}^{1-NCCR}$ are the expected net present value of the CCR plant and the Non-CCR plant in period T_1, which can be obtained from Eq. (21).

Then the decision between building a CCR plant and building a Non-CCR plant is governed by

$$\begin{cases} \text{Build Non-CCR plant}, \ \text{if } S^{CCR}_{T_0} \le S^{NCCR}_{T_0} \\ \text{Build CCR plant}, \ \text{if } S^{CCR}_{T_0} > S^{NCCR}_{T_0} \end{cases} \tag{25}$$

2.3. Solution to the model

There are several numerical methods that could be used to simulate the uncertainties and solve the model, e.g. lattice methods and Monte Carlo simulation methods (Cox et al., 1979; Brandão and Dyer, 2005; Judd, 1998). In this work, we use Monte Carlo methods to simulate the evolution of the multidimensional uncertainties described in Section 2.1, and we then employ dynamic programming methods to solve the model recursively from period T to T_0. In particular, to improve the accuracy of the estimation of the continuation values $E_t(V_t^1)$, $E_t(V_t^2)$, $E_t(V_t^3)$ and $E_t(NPV_t)$, we use the least squares Monte Carlo simulation methods proposed by Longstaff and Schwartz (2001) and widely employed by Gamba and Fusari (2009), Cortazar et al. (2008), etc. To be more specific, we first regressed the economic values in each period (V_t^1, V_t^2, V_t^3 and NPV_t) on a linear combination of a set of basic functions of

[10] Appendix A shows in detail how CF_j^{BR} is calculated.

[11] For details on how to calculate the net cash flow in each period CF_k^{BETS}, see Appendix A.

Table 1
Technical parameters.

Installed capacity (MW)		600
Construction cycle (years)		2
Average capacity load (%)		85
Plant life cycle (years)		35
Emissions factors (t CO_2/MWh)		0.79
Initial capital outlay (million RMB)	Non-CCR plant	3165.8
	CCR plant	3482.3
Additional capital outlay for CCS retrofit (million RMB)	Non-CCR plant	1449.9
	CCR plant	778.8
Initial O&M cost (million RMB)	Non-CCR plant	165.3
	CCR plant	181.8
Additional O&M cost for CCS operation (million RMB/y)	Non-CCR plant	115.7
	CCR plant	71.1
Initial power supply efficiency (%)		42
Efficiency penalty with CCS (percentage points)	Non-CCR plant	9.5
	CCR plant	8.5
CO_2 capture rate (%)		80
Transport, storage, and monitoring costs (RMB/t CO_2)		50
Time needed for CCS retrofit (year)		1

Data sources: Sekar (2005), Liang et al. (2009), Rohlfs and Madlener (2011).

Table 2
Economic parameters.

Parameters		Value
Initial electricity price (RMB/MWh)		330
Initial coal price (RMB/M Btu)		25
Risk-adjusted electricity price drift rate (%)		3
Risk-adjusted coal price drift rate (%)		3
Electricity price volatility (%)		5
Coal price volatility (%)		10
Initial carbon price (RMB/t CO_2)		50
Risk-adjusted carbon price drift rate (%)		5
Carbon price volatility (%)		15
Correlation coefficient	Electricity-coal	0.6
	Electricity-carbon	0.395
	Coal-carbon	−0.35
Discount rate (%)		5
Time of introducing carbon pricing		2017
Time step length in simulation (year)		1/4
Number of simulated paths		10,000

Data source: Abadie and Chamorro (2008), Liang et al. (2009), Rohlfs and Madlener (2011) and Mo et al. (2016).

stochastic variables (coal price P_{1-t}, electricity price P_{2-t} and carbon prices P_{3-t}):

$$\begin{cases} V_t^i = a_i + b_iP_{1-t} + c_iP_{2-t} + d_iP_{3-t} + e_iP_{1-t}^2 + f_iP_{2-t}^2 + g_iP_{3-t}^2 \\ \quad + h_iP_{1-t}P_{2-t} + k_iP_{1-t}P_{3-t} + l_iP_{2-t}P_{3-t} + \varepsilon_{i-t}, (i = 1, 2, 3); \\ NPV_t = a_4 + b_4P_{1-t} + c_4P_{2-t} + d_4P_{3-t} + e_4P_{1-t}^2 + f_4P_{2-t}^2 + g_4P_{3-t}^2 \\ \quad + h_4P_{1-t}P_{2-t} + k_4P_{1-t}P_{3-t} + l_4P_{2-t}P_{3-t} + \varepsilon_{4-t} \end{cases} \tag{26}$$

We can then estimate the parameters in the equations above (a_i, b_i, c_i, d_i, e_i, f_i, g_i, h_i, k_i, l_i; $i = 1, 2, 3, 4.$) using least squares. Relying on these estimated regression parameters and the simulated stochastic variables we calculated the estimator for the expected economic values ($E_t(V_t^1)$, $E_t(V_t^2)$, $E_t(V_t^3)$ and $E_t(NPV_t)$):

$$\begin{cases} E_t\left(V_t^i\right) = a_i + b_iP_{1-t} + c_iP_{2-t} + d_iP_{3-t} + e_iP_{1-t}^2 + f_iP_{2-t}^2 + g_iP_{3-t}^2 \\ \quad + h_iP_{1-t}P_{2-t} + k_iP_{1-t}P_{3-t} + l_iP_{2-t}P_{3-t}, (i = 1, 2, 3); \\ E_t(NPV_t) = a_4 + b_4P_{1-t} + c_4P_{2-t} + d_4P_{3-t} + e_4P_{1-t}^2 + f_4P_{2-t}^2 + g_4P_{3-t}^2 \\ \quad + h_4P_{1-t}P_{2-t} + k_4P_{1-t}P_{3-t} + l_4P_{2-t}P_{3-t} \end{cases} \tag{27}$$

To check the robustness of the results, we also included the higher order of the stochastic variables. While this significantly increased processing time, the results were very similar.

Based on the methods presented above and decision rules stipulated in Section 2.2, we can obtain the results on each of the simulated paths, e.g. whether to invest in CCR at the beginning, whether and when to retrofit the plant with CCS in future, and the carbon abatement during the entire lifetime of the plant. The presentation of our simulation results focuses on the probability of CCS retrofitting, the expected CO_2 abatement, the probability of CCR investment, and the trigger carbon prices that are intended to induce CCR investment. We first compute the probability of CCS retrofitting as the number of simulated paths in which a CCS retrofit is implemented according to Eq. (14) divided by the total number of simulated paths. The expected CO_2 abatement is simply the average of the CO_2 abatement amounts during the entire lifetime of the plant obtained on all the simulated paths, based on Eq. (A.14). The probability of CCR investment is computed as the number of paths along which a CCR plant is the optimal choice, based on Eq. (25) divided by the total number of simulated paths. Finally, we calculate the trigger carbon price as the carbon price level above which the probability of building a CCR plant is greater than that of building a Non-CCR-plant, or more specifically the carbon price level above which the probability of building a CCR plant is higher than 50%. That is, for carbon prices that exceed the trigger price, the investor is more likely to choose a CCR plant than a Non-CCR plant.

3. Case study

China is the world's largest emitter of greenhouse gases, and the power sector contributes about 50% of China's total energy-related CO_2 emissions (IEA, 2013c). Several studies suggest that a significant number of thermal power plants need to be built to meet future electricity demand in China, which is expected to grow rapidly (e.g. IEA, 2012). For our case study simulations, we chose a supercritical pulverized coal (SCPC) plant, as it is a mature technology, and is currently the dominant option for new coal-fired power plants in China (IEA, 2010b; Wang and Du, 2016). Tables 1 and 2 display the relevant technical and economic parameters for a CCR plant and a Non-CCR plant.[12]

4. Simulation results

In this section, the impact of initial CCR investment on future CCS retrofitting and CO_2 abatement is presented, and then the key factors driving current CCR investment are explored.

4.1. The impact of CCR investment on CCS retrofit and CO_2 abatement

We first analyze the impact of the initial CCR investment on a future CCS retrofit and CO_2 abatement for a range of initial carbon prices (see Table 3). Our range of carbon prices reflects the carbon prices observed in the carbon emission trading pilot schemes in China. These prices range from 20 RMB/t CO_2 to 120 RMB/t CO_2, with an average carbon price of about 50 RMB/t CO_2. Even in the low carbon price scenario (20 RMB/t CO_2) the probability of a CCS retrofit for the CCR plant is quite high (about 86%), and increases with a higher initial carbon price. For all initial carbon prices considered, the probability of a CCS retrofit for a CCR plant is higher than that for a Non-CCR plant. In addition, we calculate the difference in the probability of a CCS retrofit between a CCR plant and a Non-CCR plant over a range of carbon price levels. As shown in Table 3, this difference increases for lower carbon prices. While this result is unsurprising per se, it also implies that the effect of

[12] The exchange rate used is 1 USD = 6.5 RMB, which was taken from the Bloomberg website in January 2016. Since there currently is no futures market in China, and the spot market is still regulated, most parameters shown in Table 2 are taken from the literature (i.e. Abadie and Chamorro, 2008; Liang et al., 2009; Rohlfs and Madlener, 2011; Mo et al., 2016)). Thus, the parameters are based mainly on data from mature spot and futures markets such as the European Energy Exchange and the European Climate Exchange.

Table 3
The impact of initial CCR investment on future CCS retrofitting and CO_2 abatement.

Initial carbon prices (RMB/t CO_2)		20	40	60	80	100	120	140
Probability of CCS retrofit (%)	CCR	86.0	89.1	92.4	95.0	96.1	96.2	96.6
	Non-CCR	73.0	76.2	81.3	86.8	90.1	91.1	91.5
Difference in probability (% points)		13.0	12.9	11.1	8.2	6.0	5.1	5.1
CO_2 abatement (Mt CO_2)	CCR	1.7	9.5	20.2	31.7	42.4	52.0	60.1
	Non-CCR	1.2	7.8	16.8	26.5	35.7	43.1	49.1
Difference in CO_2 abatement (Mt CO_2)		0.5	1.7	3.4	5.2	6.7	8.9	10.9

CCR investment on a CCS retrofit in the future is more significant if the carbon price is low. Finally, for all carbon prices considered, the CO_2 abatement by the plant is also higher for the CCR plant than for the Non-CCR plant. As expected, CCR investment in the initial stage increases CO_2 abatement. For higher carbon prices considered, the difference in abatement is also greater because the plant is more likely to be operated in CCS mode (and abate more emissions) with high carbon prices than with low carbon prices.

4.2. Effects of allowing for CCS operating flexibility

Since a novel aspect of the model is that we allow for CCS operating flexibility in the investment decision under the carbon emission trading scheme, we explored the impact of this flexibility on CCS retrofitting, CO_2 abatement, and especially the CCR investment decision. As shown in Fig. 2, the probability of a CCS retrofit is higher with CCS operating flexibility than without such flexibility for both the CCR plant and the Non-CCR plant in all carbon price scenarios. With CCS operating flexibility incorporated in the model, the investor can switch off CCS operation and instead purchase CO_2 certificates on the market if carbon prices are low. In essence, the operating flexibility cushions the irreversibility of the CCS retrofit investment, thereby increasing the propensity to invest in a CCS retrofit. Fig. 2 further illustrates that the effect of operating flexibility on CCS retrofitting is greater for lower initial carbon prices, indicating that operating flexibility should not be neglected in the current situation.

In principle, operating flexibility has two countervailing effects on CO_2 abatement. First, as just discussed, operating flexibility promotes CCS retrofitting, which then increases the possibility of abating CO_2 emissions. Second, operating flexibility enables investors to suspend CCS operation and CO_2 abatement temporarily if future market conditions are not favorable. The net effect on emission abatement depends on the relative magnitude of these countervailing effects of operating flexibility. As shown in Fig. 3, the amount of CO_2 abated with operating flexibility is less than that without CCS operating flexibility, which indicates that for our scenarios the latter effect dominates. Consequently, although CCS operating flexibility promotes CCS retrofitting, it decreases the amount of CO_2 abated. Fig. 3 further suggests that the magnitude of this effect varies with the carbon price. For the CCR plant, the difference is greatest for carbon prices of 60 and 80 RMB/t CO_2 and significantly smaller for the lower and higher carbon prices considered.

CCS operating flexibility affects the current decision regarding plant type by affecting future CO_2 abatement and CCS retrofitting. Fig. 4 displays the impact of CCS operating flexibility on the decision between investing in a CCR plant or a Non-CCR plant. Accordingly, the probability of investing in a CCR plant is higher when the plant does not allow for operating flexibility. Thus, operating flexibility renders a CCR plant less attractive. Fig. 4 further suggests that the hampering effect of operating flexibility on CCR investment is weaker for low carbon prices and high carbon prices in our scenarios and peaks at a price of 90 RMB/t CO_2. Current research on the interaction of options concludes that there are "decreasing returns" to additional flexibility. Thus, adding flexibility when there are multiple options contributes less to the valuation of an investment than when there is a single option only (Trigeorgis, 1993).

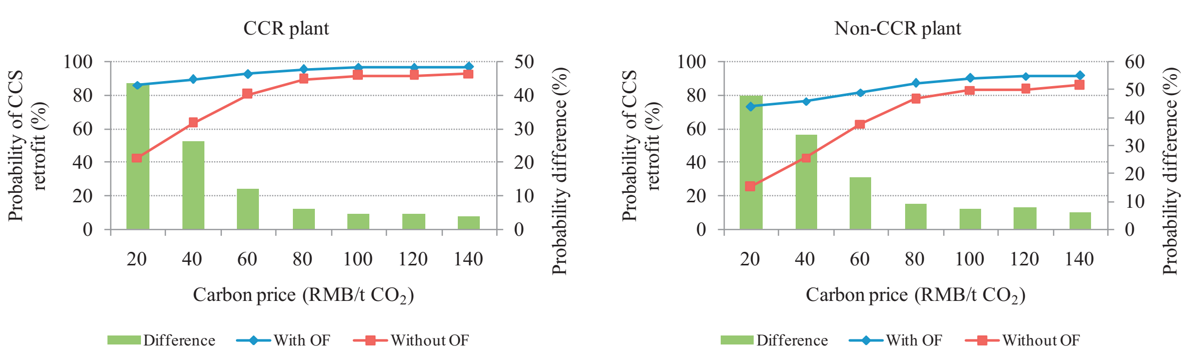

Fig. 2. The effect of operating flexibility (OF) on CCS retrofitting.

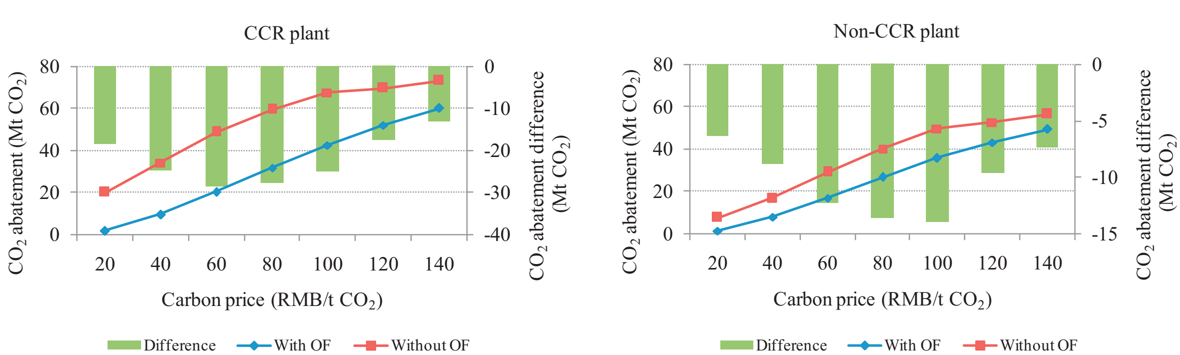

Fig. 3. The effect of operating flexibility (OF) on CO_2 abatement.

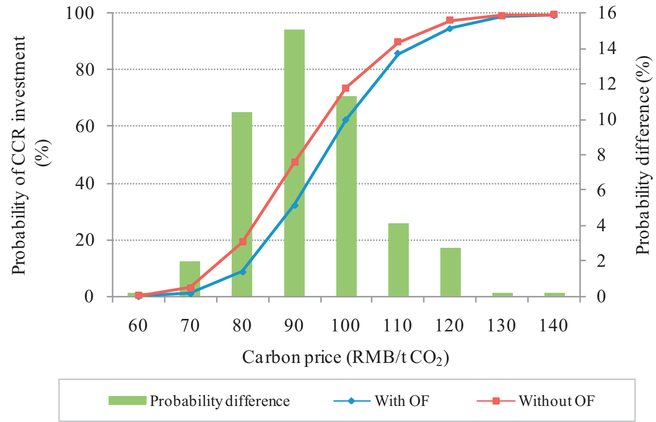

Fig. 4. The impact of the operating flexibility (OF) on CCR investment.

In comparison, our simulation results illustrate that the contribution of one additional option has to be assessed within the specific context of the market and policy environment.

4.3. Other key factors driving CCR investment

In this section, we analyze other key factors affecting the choice between building a CCR plant or a Non-CCR plant. We further calculate the trigger carbon prices under a range of market and policy conditions.

4.3.1. Carbon prices

The carbon price level and carbon price risk shape the decision to invest in a CCR plant by affecting CCS investment and operation. The left panel of Fig. 5 shows the CCR investment probabilities for scenarios at various carbon price levels and carbon price volatilities (10%, 15%, 20%, and 25%). As expected, higher carbon price volatility discourages investment in CCR plants. Fig. 5 further suggests that, under current average prices observed in China's pilot schemes, i.e., 50 RMB/t CO_2, investment in CCR plants is rather unlikely, even if the volatility of the carbon price is low.

The right panel of Fig. 5 illustrates that the trigger carbon price is higher under higher carbon price volatility and increases at an increasing rate. By definition, the trigger price curve seen in Fig. 6 describes the combinations of initial carbon prices and carbon price volatility, where the investor is indifferent between investing in a CCR plant and investing in a Non-CCR plant. In the base case scenario of carbon price volatility (15%), the trigger carbon price is about 92 RMB/t CO_2, which is higher than the current average carbon price in China's ETS pilots.

4.3.2. Timing of introducing carbon pricing policy

Even when a country or a region has announced the introduction of an ETS, the timing may be uncertain. For example, when the Chinese national ETS was originally announced it was set to start in 2015, but it was unlikely to get off the ground before the end of 2017. We therefore explore how the timing of an ETS introduction will affect the plant type choice. The left panel of Fig. 6 shows that, over a range of carbon price paths, the later an ETS is introduced the lower is the probability of CCR investment. The effects of the delay of an ETS are weaker for higher carbon prices. If the ETS is introduced after 2025, however, the probability of CCR investment is virtually zero for all carbon price paths.

The right panel of Fig. 6 shows that the trigger carbon price increases at an increasing rate with the delay of introducing an ETS.

4.3.3. CCR investment cost

CCR is not a specific plant design; it is more accurate to say that it denotes a spectrum of investment and design decisions with varying levels of CCR investment (IEA, 2007b; Bohm et al., 2007). The spectrum includes leaving some essential space next to a plant for CCS

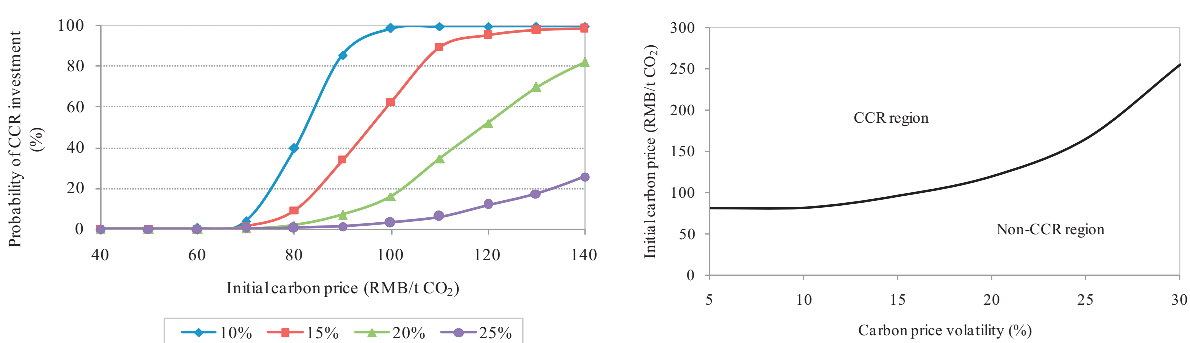

Fig. 5. The impact of carbon prices on CCR investment decisions and trigger carbon prices in a range of carbon price volatility scenarios.

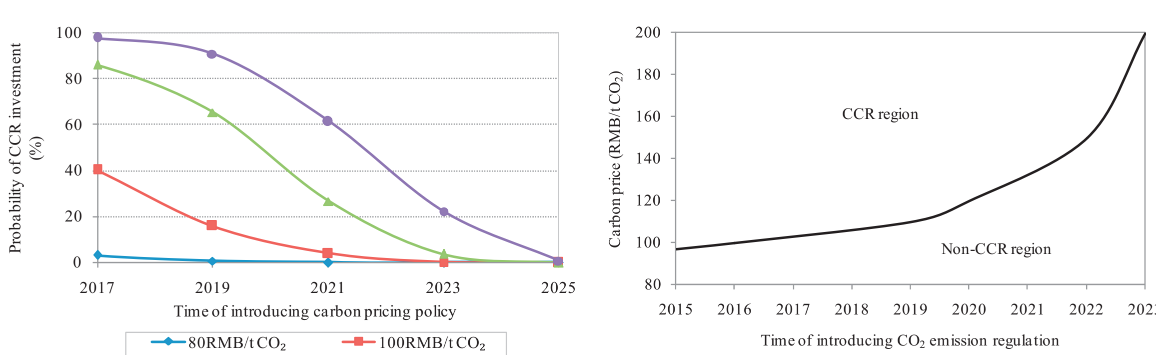

Fig. 6. The impact of the timing of carbon ETS introduction on CCR investment decision and trigger carbon prices over a range of carbon ETS introduction timing.

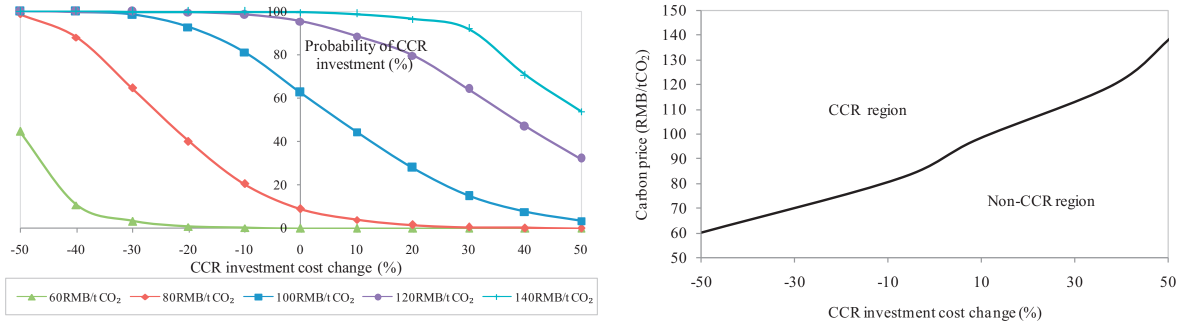

Fig. 7. The impact of CCR investment costs on the CCR investment decision and trigger carbon prices over a range of CCR investment cost levels.

retrofitting or adding some extra systems, equipment, and modifications (Rohlfs and Madlener, 2013). Thus the investment costs involved in CCR may vary widely depending on the original design and location of a plant.

The left panel of Fig. 7 shows that higher CCR investment costs lower the probability of investing in a CCR plant. This decline in probability is stronger for lower carbon prices. For low carbon prices of 60 RMB/t CO_2, i.e., price levels in the range of those typically observed in China's ETS pilot programs, the probability of investing in CCR approaches 50% only if CCR investment costs are less than half the baseline value. Likewise, if CCR investment costs exceed the baseline costs by 50%, the probability that the CCR plant is chosen in Stage 1 exceeds 50% only for initial carbon prices of about 140 RMB/t CO_2 and higher. These results further confirm the findings by Bohm et al. (2007), Liang et al. (2009) and Rochedo and Szklo (2013) that only moderate CCR investment is economically viable.

According to the right panel of Fig. 7 the trigger carbon price increases almost linearly with higher CCR investment costs. These results also imply that the carbon price currently observed in China's ETS pilots can support only low levels of CCR investment.

4.3.4. Learning effects of CCS technology

A high up-front investment cost is a barrier to the diffusion of CCS technology. Because of the learning (curve) effects, however, these costs are likely to come down over time (Lohwasser and Madlener, 2013; Murphy and Edwards, 2003). The left panel of Fig. 8 presents our findings regarding the impact of technological learning for CCS technology on plant type choice in Stage 1. The learning rate is expressed as a percentage point decrease in the investment cost per year. Because CCS has so far not been employed on a large scale, the learning rate associated with CCS cannot be based on empirical figures. Instead, we rely on findings pertaining to related technologies as a reference point. According to Lohwasser and Madlener (2013), the average annual learning rate associated with flue-gas desulfurization between 1970 and 2000 was about 4.5%. Given the uncertainty of the learning effect, our analysis considers learning effects in a range of 1%–10%. As shown in the left panel of Fig. 8, for all carbon price paths higher learning rates lower the probability of investing in CCR. This decline is greater for lower carbon prices. If the learning effects associated with CCS technology are significant, future CCS investment costs decrease rapidly, and CCS retrofitting becomes economically viable even for Non-CCR plants. In this sense, high CCS learning rates diminish the value of CCR.

The right panel of Fig. 8 illustrates that the trigger carbon price increases roughly linearly with the CCS learning rates.

4.3.5. Electricity prices

Electricity prices in China are currently rather low because of government regulations but are expected to increase in the wake of an ongoing reform program that is designed to increase market orientation. Higher electricity prices mean higher revenues and higher profits for investors in CCR and Non-CCR plants (the revenue effect). However, higher electricity prices also imply higher opportunity costs associated with the loss of efficiency when a plant runs in CCS mode. In such a case—unless the capacity load factor is increased (via additional investments) after a retrofit—less electricity will be generated and sold by the plant (the efficiency loss effect). Thus, in general, the net effect of higher electricity prices on CCR investment is driven in opposite directions by two factors, i.e. the revenue effect and the efficiency loss effect. Our simulation results (see the left panel of Fig. 9) suggest however that the probability of investing in a CCR plant is lower for higher electricity prices. Thus, the efficiency loss effect dominates the revenue effect in our scenarios.

As shown in the right panel of Fig. 9, the trigger carbon price increases almost linearly with the electricity price. Currently, on-grid electricity prices across Chinese provinces range from 300 RMB/MWh to 500 RMB/MWh. Based on our calculations, these electricity prices correspond to a trigger price of between 85 RMB/t CO_2 and 130 RMB/t CO_2, which is substantially higher than the average carbon price observed in the pilot schemes.

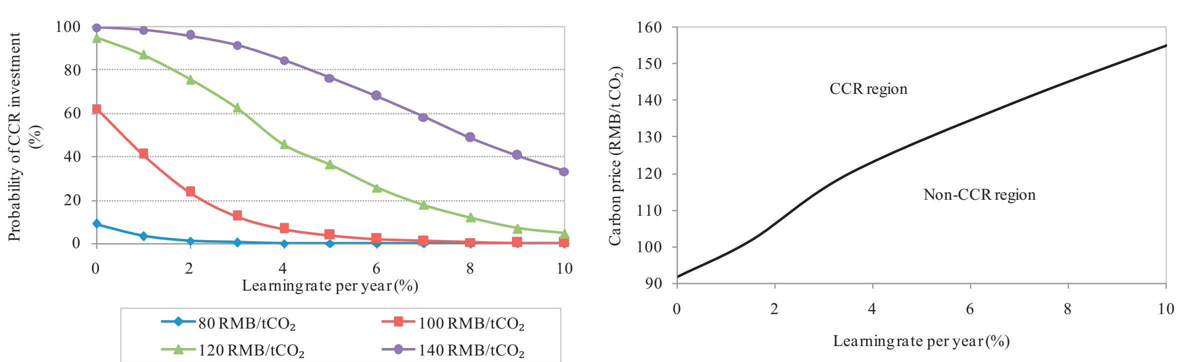

Fig. 8. The impact of CCS learning effects on CCR investment and trigger carbon prices over a range of CCS learning rates.

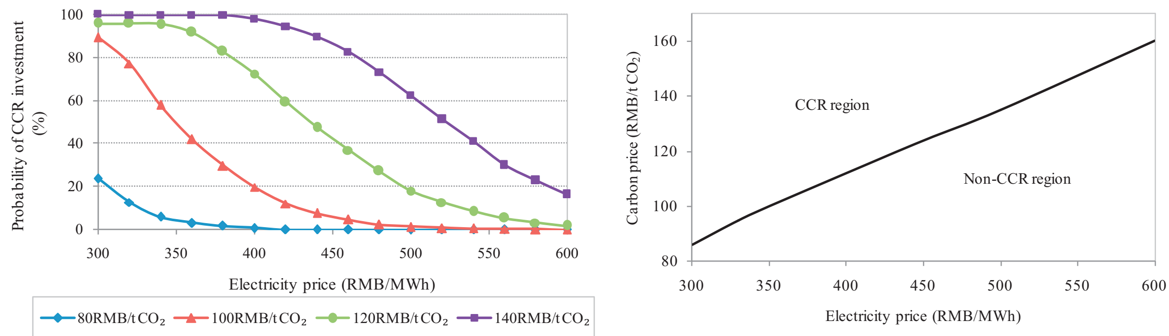

Fig. 9. The impact of electricity prices on CCR investment and trigger carbon prices for different electricity price scenarios.

5. Discussion and conclusion

To limit the economic risks associated with stringent future climate policies, plant investors may decide to invest in CCR rather than in conventional Non-CCR plants. A CCR plant involves higher current investment costs than a Non-CCR plant, but it can be retrofitted with CCS technology at relatively low additional costs at any time in the future. So the plant type choice is a critical issue for potential plant investors. This paper develops a novel three-stage CCR investment decision model, which incorporates uncertainty in fuel, electricity, and carbon prices and accounts for various flexibilities. The latter include the flexibility to decommission a plant in advance, flexibility in the timing of a CCS retrofit, and, in particular, operating flexibility. Thus, depending on market conditions, plant operators may decide to run a plant in CCS mode to abate CO_2 emission or in CCS-off mode to avoid efficiency losses. We parameterize the model to mimic investment in a new supercritical pulverized coal plant in China. The model is solved via least squares Monte Carlo simulation methods.

5.1. Main findings

Our simulation results confirm that investing in CCR spurs future CCS retrofitting and thus increases CO_2 abatement by a plant. This effect is stronger for lower carbon prices. Thus, CCR may help promote future CCS retrofitting, in particular, if—as is currently the case in most ETSs—carbon prices are low. Somewhat surprisingly, we find that allowing for operating flexibility may reduce CCR investment. Thus, analyses ignoring a plant operator's option to temporarily suspend CO_2 abatement and instead to purchase the required CO_2 certificates on the market may overestimate the economic viability of CCR and its potential to abate CO_2 emissions. We further show that the magnitude of this effect depends on the level of the carbon price. For carbon prices below 60 RMB/t CO_2 or above 140 RMB/t CO_2 the overestimation is rather negligible. But for carbon prices observed in the Chinese ETS pilot schemes this bias would be significant.

Our simulation results also show that if CCS investment costs drop significantly over time (e.g., because of technological learning), investors are less likely to invest in a CCR plant. Thus, government efforts to lower the costs of CCS via support for research, development, and demonstration projects may impede investments in CCR.

The findings of our simulations further suggest that high electricity prices are likely to inhibit investment in CCR. The negative opportunity cost effect, which results from the loss in output that occurs when running a plant in CCS mode exceeds the positive effect of higher revenues, comes into play to discourage such investment. Thus, electricity price increases, such as those envisaged in China in the wake of electricity market reforms, will, accordingly, likely discourage investment in CCR. This finding highlights the need for policymakers to take into account interaction between the electricity market and the carbon market.

Finally, the results of the case study implies that CCR investment does not appear to be economically viable under current conditions in China because of a low carbon price, high carbon price risk, the high cost of CCR investment and the high opportunity cost of CCS operation. The trigger carbon price supporting the CCR investment in the base case is about 92 RMB/t CO_2, which is still higher than the current average carbon price in China's pilot ETSs.

5.2. Policy implications

Our simulation results show that the impact of policy measures on CCR investment and CCS investment may be complex. Some policies can promote CCR and CCS simultaneously, such as starting a carbon pricing policy early, tightening the carbon budget to maintain a high carbon price, and implementing market-stabilizing measures to lower the carbon price risk. Other policy measures imply a trade-off between investments in CCS and investments in CCR. For example, allowing CCS operating flexibility in the future can promote investment in CCS, but may restrain investment in CCR. Whether policymakers should allow this flexibility in practice depends on their objectives. On the one hand, if policymakers want to promote CCR investment, they should inhibit operating flexibility and make CCS operation mandatory. On the other hand, if they want to promote immediate investment in CCS, they should allow operating flexibility. Policymakers could also promote the sharing of CCS-related knowledge among potential investors, in particular regarding the technological options involved in operating the plant in flexible mode. Policies supporting research and development may bring down the cost of CCS investment and thus promote CCS development, but they will also restrain early investment in CCR. To avoid countervailing effects and to maximize the net benefits over time, policies designed to promote CCR and CCS deployment need to be coordinated.

5.3. Limitations and extensions

The results presented in this paper were based on simulations for an SCPC plant in China. Using other technologies would not alter the main qualitative findings. For other technologies, though, the conclusions pertaining to the economic viability of CCR investment and the critical carbon prices supporting the CCR investment may be different, since other technologies have different costs for plant construction, additional CCR, CCS retrofit and operating. In addition, while the conceptual model developed for the CCR investment decision process applies to any country, application of the GBM model of the electricity and coal price dynamics may be limited to the countries like China, where the energy prices are currently regulated and low, yet are expected to increase in the future. When this model is used for countries where energy markets are liberalized, a mean reverting process is more appropriate. Since China has begun implementing market-oriented reforms, future analyses of CCR investment may also use a mean-reverting process to adequately reflect the new situation in energy markets. Ideally, model parameterization may then also capitalize on mature spot and futures markets.

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Appendix A. Calculation of cash flow and CO_2 abatement

The cash flow for a plant in period iCF_i can be expressed as

$$CF_i = R_{e-i} - C_{fuel-i} - C_{om-i} - C_{TS-i} - C_{CO_2-i} \tag{A.1}$$

where R_{e-i} is the revenues from electricity sales, C_{fuel-i} is the fuel cost, C_{om-i} stands for the costs of operation and maintenance (O&M), C_{TS-i} reflects the costs of transportation and sequestration of CO_2, and C_{CO_2-i} stands for the costs of acquiring CO_2 certificates. We assume that no certificates are allocated for free. Also, the investor takes prices in all input and output markets as given.

Before carbon pricing, i.e. carbon ETS, is introduced (BETS), $C_{TS-i} = C_{CO_2-i} = 0$, and

$$CF_i^{BETS} = R_{e-i}^{BETS} - C_{fuel-i}^{BETS} - C_{om-i}^{BETS} \tag{A.2}$$

After the ETS is introduced and before the plant is retrofitted with CCS (BR), $C_{CO_2-i} > 0$, and

$$CF_i^{BR} = R_{e-i}^{BR} - C_{fuel-i}^{BR} - C_{om-i}^{BR} - C_{CO_2-i}^{BR} \tag{A.3}$$

After the ETS is introduced and the plant is retrofitted with CCS, operating the plant in CCS mode (CC) means lower revenues from electricity sales, higher costs for O&M, additional costs for transportation and sequestration, but lower costs for acquiring certificates. In this case

$$CF_i^{CC} = R_{e-i}^{CC} - C_{fuel-i}^{CC} - C_{om-i}^{CC} - C_{TS-i}^{CC} - C_{CO_2-i}^{CC} \tag{A.4}$$

If investors suspend CCS (SCC), O&M costs drop and $C_{TS-i} = 0$, but certificate costs are higher. In this case

$$CF_i^{SCC} = R_{e-i}^{SCC} - C_{fuel-i}^{SCC} - C_{om-i}^{SCC} - C_{CO_2-i}^{SCC} \tag{A.5}$$

Investors can sell the same amount of electricity N_{e-i}^{NCCS} in non-CCS mode as they did before the CCS retrofit, so revenues are

$$R_{e-i}^{BETS} = R_{e-i}^{BR} = R_{e-i}^{SCC} = N_{e-i}^{NCCS} \times P_{e-i} \tag{A.6}$$

where P_{e-i} is the electricity price in period i. Operating in CCS mode leads to lower electricity generation than N_{e-i}^{NCCS}. In this case the revenue is

$$R_{e-i}^{CC} = N_{e-i}^{CCS} \times P_{e-i} \tag{A.7}$$

In each scenario the fuel input (coal consumption) is the same, N_{co-i}. Thus fuel costs are

$$C_{fuel-i}^{BETS} = C_{fuel-i}^{BR} = C_{fuel-i}^{SCC} = C_{fuel-i}^{CC} = N_{co-i} \times P_{co-i} \tag{A.8}$$

where P_{co-i} is the price of coal in period i.

CO_2 emissions are $N_{CO_2-i}{}^{NCCS}$ before a CCS retrofit, and also after a CCS retrofit in non-CCS operation mode. The costs of acquiring certificates are then

$$C_{CO_2-i}^{BETS} = C_{CO_2-i}^{BR} = C_{CO_2-i}^{SCC} = N_{CO_2-i}^{NCCS} \times P_{CO_2-i} \tag{A.9}$$

where P_{CO_2-i} is the carbon price in period i.

In CCS operation mode, CO_2 emission $N_{CO_2-i}{}^{CCS} < N_{CO_2-i}{}^{NCCS}$ and

$$C_{CO_2-i}^{CC} = N_{CO_2-i}^{CCS} \times P_{CO_2-i} \tag{A.10}$$

Note that $N_{CO_2-i}{}^{CCS} > 0$, reflecting a capture rate of <100%. The amount of CO_2 abated under the CCS mode, N_{CAA-i}, is then

$$N_{CAA-i} = N_{CO_2-i}^{SCC} - N_{CO_2-i}^{CC} \tag{A.11}$$

In CCS mode the costs of CO_2 transportation and sequestration are

$$C_{TS-i}^{CC} = c_{TS}^{CC} \times N_{CAA-i} \tag{A.12}$$

where c_{TS}^{CC} are the per-unit costs of CO_2 transportation and sequestration.

Before the plant is retrofitted with CCS, CO_2 abatement is 0; after the plant is retrofitted it is N_{CAA-i} in CCS operation mode, and 0 in non-CCS operation mode. Thus, the level of CO_2 abatement in period i N_{C-i} can be described by

$$N_{C-i} = \left\{ \begin{array}{ll} 0, & when\ T_0 \le i \le T_r \\ \left. \begin{array}{ll} 0, & if\ CF_i^{SCC} \ge CF_i^{CC} \\ N_{CAA}, & if\ CF_i^{SCC} < CF_i^{CC} \end{array} \right\} & when\ T_r < i \le T \end{array} \right\} \tag{A.13}$$

The total amount of CO_2 abated during the lifetime of the plant is

$$N = \sum_{i=0}^{T} N_{C-i} \tag{A.14}$$

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