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Modeling the Diffusion of Carbon Capture and Storage under Carbon Emission Control and Learning Effects

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Abstract

This paper examines the interrelationship of learning effects and emission control on the diffusion of carbon capture and storage (CCS). We introduce a dynamic model in which an electricity producer maximizes profits subject to emissions control. All technologies are characterized by specific linear marginal costs and CO₂ emissions which need to be covered by limited emission permits. The fossil fuel-based plants can be replaced by the CCS technology which is associated with higher capital costs and a lower system efficiency. Both parameters improve due to learning effects if the technology is applied. The model is formulated as a non-linear optimization problem, and solved using GAMS. Given the assumed technological data, the results for a data set of Germany show that CCS is essential to reach carbon emission goals. However, particularly in the case of learning, CCS can help renewable technologies to become competitive.

JEL classification: H23; O30; Q40

Keywords: Carbon capture and storage; CCS; Climate policy; Learning

1 Introduction

The Kyoto Protocol sets a price on carbon dioxide (CO₂) emission. Participating economies are obliged to limit those emissions, with CO₂-emitting firms now facing an additional constraint in their profit maximization. The energy sector is particularly afflicted, since the combustion of fossil fuels emits massive amounts of CO₂. Presently, CO₂ allowances are limited, a factor which increases pressure on the industry, especially electricity generators, to switch to renewable or lower-carbon fuels.

Coal has the largest reserves (thus assuring future fuel availability at comparably low costs) but emits the most CO₂ per MWh_{el}. Therefore, innovative technologies to capture and store CO₂ are in development. However, they come

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with significantly higher capital cost for the plants and high energy losses in generation. Consequently, high carbon prices are required to incentivize investment in new capture and storage technologies, until costs and performance have improved due to expected learning effects and economies of scale.

The research of the economics of carbon emissions reduction is already very extensive. Related research emphasizes mainly policy instrument choices, regulation, and technology choice. These foci are then considered under different assumptions, e.g., regarding innovation, learning, uncertainty, and market imperfections. One important stream of the literature emphasizes the change in policy instruments in the case of learning. Clarke et al. (2006) analyze the sources of technological change itself by reviewing the economic literature. They emphasize the important role of learning effects and spillovers. Fischer et al. (2003) compare the choice of policy instruments for environmental protection under technological innovation and find that in this case selecting the optimum instrument depends on the characteristics of the innovation process. Rosendahl (2004) focuses on cost-effective environmental policy under induced technological change taking into account learning-by-doing (LBD). He concludes that cost-effective environmental policy does not require equal Pigouvian taxes across emission sources if external LBD effects exist. Hence, optimal emission taxes may be higher in industrialized countries. Kverndokk et al. (2004) examine the welfare implications of using taxes or subsidies to reduce carbon emissions in the presence of learning effects. They conclude that emission taxes should be favored as subsidies to an existing energy technology may hinder the entry of new and better technologies. Another important stream of the literature which is not stressed in this paper emphasizes the uncertainty aspect of learning and technological progress for environmental protection (see Böhringer et al. (2009) for a short overview and the annotated bibliography for a further discussion).

Learning effects for innovative energy-related technologies, however, have long been identified as a pivotal element for the transformation of the sector and for the success of mitigating climate change (IEA, 2000). Endogenous technical change has been incorporated in all kinds of energy system models analyzing transformation pathways of the energy sector and the impact of environmental and technology policies, e.g., linear activity analysis (MARKAL, Barreto (2001)) and non-linear partial equilibrium models (POLES, Russ and Criqui (2007)) and hybrid energy-macro models (MESSAGE, Rao et al. (2006); MERGE Kypreos (2005)). All conclude that learning rates for environmental technologies result in a much earlier and more rapid reduction in greenhouse gases and lower the social costs of climate change mitigation.¹

Nonetheless, learning effects are not limited to innovation. Mature technolo-

¹Although learning effects are crucial for the success of new technologies, they may also impede diffusion. Jensen (1980) analyzes adoption incentives for two firms under uncertainty about the future profitability of the innovation. Particularly in markets in which innovators are outside firms and close collaboration between innovator and user are required to further advance technology, early adopters are likely not to be the only ones to benefit from the learning investment. Therefore, they may also have incentives by waiting to adopt, letting others pay for the learning effect. Hence, Jensen cannot confirm the general macroeconomic finding that states that expected learning effects promote or at least accelerate technological change. In his microeconomic model learning hinders the introduction of new technologies in case of a duopolistic market structure. However, Tauri and Polasky (2005) argue that strategic behavior in the presence of learning can be overcome with a sufficiently sophisticated regulatory policy.

gies experience only limited advance, for instance through new components in the overall system. As those improvements are rather incremental, they might be offset by increasing prices for raw materials or labor, resulting more in a stable price for the technology instead of significant cost reduction. We therefore assume constant capital costs for mature technologies, with a high cumulated capacity stock installed. With respect to plant efficiency, the situation may look different. Even for mature technologies like hard coal or lignite power plants, in the past efficiency improved steadily, albeit at a decreased rate due to physical and materials limitations (Fischedick et al., 2008). Yet, completed or ongoing learning for incumbent technologies increases the cost threshold for innovations. Consequently, reaching the break-even point becomes increasingly difficult, which implies a high risk of locking out promising technologies for the future.

With respect to environmental technologies, policy-makers have at least two options. First, they can lower the cost threshold for the innovation by introducing a fee on emissions, internalizing negative pollution externalities. Second, they can support low-carbon technologies by means of tax credits, investment support, feed-in subsidies or introduce portfolio or technology standards. By doing so, they create incentives for the initial application of the innovative technology, which is required to start the learning process.

The main difficulty when dealing with experience curves is their high sensitivity to the starting point and the progress ratio (Barreto, 2001). Ex-post data for similar, or at least closely related, technologies cannot always be considered a reliable estimator of the potential of innovative solutions. Table (1) shows historical learning rates for power plant-related technologies, which indicate that the learning rate the capital costs of CCS can be in the range of 10%.

Table 1: Summary of learning rates for capital costs of CCS

Technology	Learning rate	Initial cost increase
Flue gas desulphurization (FGD)	0.11	Yes
Selective catalytic reduction (SCR)	0.12	Yes
Combined cycle gas turbine (CCGT)	0.10	Yes
Pulverized coal (PC) boilers	0.05	n/a*
LNG production	0.14	Yes
Oxygen production	0.10	n/a*
Hydrogen production	0.27	n/a*

* n/a = not available

Source: (Rubin et al., 2006)

More difficult to determine are the subsequent efficiency improvements for the technology. As the expected efficiency penalty for the CCS options is still uncertain, the same holds for potential improvements. We therefore assume an increase of 2.5% efficiency improvement for each doubling of cumulative output in our modeling.

The research objective of this paper is to examine the interplay of learning effects and emission control on the diffusion of CCS. The results show that CCS must play an important role for achieving CO₂ emission reduction goals. Given the assumed technological data, CCS is essential to reach carbon emission

goals. However, particularly in the case of learning, CCS can help renewable technologies to become competitive. The remainder of this paper is structured as follows. Section 2.1 presents the basic nonlinear optimization model formulation. In Section 2.2, the model is extended by learning rates. Both models are then applied to a realistic data set (Section 2.3) to analyze the process of CCS market diffusion in different scenarios (Section 3). Section 4 concludes the paper.

2 Model Descriptions and Data

2.1 Benchmark model

We model the diffusion of CCS technologies in a perfect competitive market. Demand is given by a linear demand function:

$$D_t(P_t) = a_t - b_t P_t \quad \forall t \quad (1)$$

P_t is the electricity demand in period t and $a_t, b_t > 0$ are parameters defining the demand function. Consequently, the inverse demand function is given as:

$$P_t(D_t) = \frac{a_t - D_t}{b_t} \quad \forall t \quad (2)$$

Since the electricity market must be cleared, demand in period t must be equal to total supply:

$$\sum_{g, \tau \leq t} X_{g, \tau, t} = D_t = a_t - b_t P_t \quad \forall t \quad (3)$$

$X_{g, \tau, t}$ is period t production of technology g with a plant installed in period τ .

Technologies are characterized by their heat efficiency $\eta_{g, \tau}$ which depends on the technology g and installation date of the plant τ . The plants are characterized by a technology-specific carbon capture rate $cpr_{g, \tau}$ which also depends on the installation date of the plant. Besides fuel costs, technologies cause further constant unit costs c_g (e.g., maintenance and repair). The price of capacity investment $ICAP_{g, t}$ is exogenously given by $pi_{g, t}$. In every period, the price of fuel f ($pf_{f, t}$) is also exogenously given.

Generation using technology g in period t is restricted by the capacity installed in period τ :

$$fl_{g, \tau, t} \Delta t CAP_{g, \tau} + flex_{g, \tau, t} \Delta t excap_{g, \tau} \geq X_{g, \tau, t} \quad \forall g, \tau, t \quad (4)$$

Where $fl_{g, \tau, t}$ are age-dependent full-load hours expressed in percentage of the period length Δt of capacity installed in period τ . The model allows us to exogenously install capacity $excap_{g, \tau}$ with corresponding full-load hours in period t $flex_{g, \tau, t}$. Full-load hours are decreasing in the age of plants to account for necessary repair and maintenance time. If the age exceeds the technology-specific lifetime the plant will be scrapped and, consequently, full-load hours become zero. An example is given below:

$$fl_{\tau, t} = \begin{pmatrix} 0.95 & 0.9 & 0.87 & 0 & 0 \\ 0 & 0.95 & 0.9 & 0.87 & 0 \\ 0 & 0 & 0.95 & 0.9 & 0.87 \\ 0 & 0 & 0 & 0.95 & 0.9 \\ 0 & 0 & 0 & 0 & 0.95 \end{pmatrix}$$

Installed capacity results from capacity investments. Depending on the technology, investments need $ilag_g$ period to become effective:

$$CAP_{g(t+ilag_g)} = ICAP_{gt} \quad \forall t \quad (5)$$

Furthermore, capacity investment is restricted by the technology-specific upper bound $imax_g$:

$$imax_g \geq ICAP_{gt} \quad \forall g, t \quad (6)$$

Period t emissions of plants using technology g (E_{gt}) are given as the sum over generation of all plants taking into account the fuel-specific carbon content (θ_f), the technology- and installation date-dependent capture rate ($cpr_{g\tau}$), and thermal efficiency ($\eta_{g\tau}$):

$$E_{gt} = \sum_{\tau, f | (g, f) \in M} (1 - cpr_{g\tau}) \theta_f \frac{X_{g\tau t}}{\eta_{g\tau}} \quad \forall g, t \quad (7)$$

The two-dimensional set M defines the mapping between technologies and the fuels used by the technology. If a technology fuel combination is an element of this set ($(g, f) \in M$), the thermal efficiency of the technology is strictly positive.

Total emissions are constrained by the exogenously set emission target $emax_t$:

$$emax_t \geq \sum_g E_{gt} \quad \forall t \quad (8)$$

We maximize the sum of future discounted welfare using the discount factor β which we set to 0.9. Welfare is calculated as the integral under the demand curve less the production cost which consists of fuel and other variable costs as well as investment cost.

$$\begin{aligned} \sum_t \beta^t \left\{ \int_0^{D_t(P_t)} P_t(D_t) dD_t \right. \\ \left. - \sum_{g, \tau \leq t} X_{g\tau t} \left[c_g + \sum_{f | (f, g) \in M, \tau \leq t} \frac{pf_f}{\eta_{g\tau}} \right] \right. \\ \left. - \sum_g pi_{g,t} ICAP_{g,t} \right\} \end{aligned} \quad (9)$$

Equation (9) is maximized subject to the constraints (1 - 8). The choice variables are generation and investment levels with installed capacity and emissions as the resulting state variables.

2.2 Model with Learning Effects

A brief discussion of learning aspects and a mathematical representation appears in Appendix A. Our adjusted model explicitly includes learning of two types. First, LBD effects on the investment price of technologies. The realization of these effects depends on cumulative capacity investments. Second, the heat efficiency of technologies is subject to a LBD effect which depends on technologies' cumulative generation. Both learning types are introduced with one factor learning curves.

For the investment price, the learning curve describes the relationship between cumulative capacity investment up to period t and investment cost for new capacity. Incorporating learning effects leads to endogenous investment cost. Therefore, investment costs are denoted by capital letters $PI_{g,t}$ in the learning model. The equation defining the investment cost becomes:

$$PI_{g,t} = pi_{g,0} \left(\frac{cap_{g,0}}{cap_{g,0} + \sum_{\tau < t} ICAP_{g,\tau} + \sum_{\tau < t} capad_{g,\tau}} \right)^{-\alpha_g} \quad (10)$$

Here, $cap_{g,0}$ and $pi_{g,0}$ are the initially installed capacities and investment costs and α_g is the learning elasticity of technology g for investment cost. Public demonstration projects or exogenous capacity investment, such as onshore wind, are taken into account by $capad_{g,\tau}$, which is exogenously added capacity. For the case of investment cost the elasticity becomes negative, i.e. an increase in cumulative investment decreases investment cost.

Furthermore, there are learning-by-using effects for the heat efficiency of technologies which depend on cumulative generation:

$$\eta_{g,t} = \eta_{g,0} \left(\frac{gen_{g,0}}{gen_{g,0} + \sum_{\tilde{\tau} < t, \tau < \tilde{\tau}} X_{g,\tau,\tilde{\tau}}} \right)^{-\gamma_g} \quad (11)$$

where $\eta_{g,0}$ is the initial heat efficiency and γ_g the learning elasticity of technology g for heat efficiency, and $gen_{g,0}$ is a parameter which expresses initial cumulative generation. For conventional technologies this parameter is high, hence the learning effect of added generation is low. Since heat efficiency is increasing in cumulative generation, the learning elasticity γ_g becomes positive.

The welfare maximizing model with technological progress is obtained by adding equations (10) and (11) to the benchmark problem.

Both models are implemented as non-linear programs in GAMS (Brooke et al., 2005).

2.3 Data

Cost and performance data for technologies are taken from the standard literature (such as Wissel et al. (2008)) and displayed in Tables 2 and 3. However, assumptions are needed for CCS. Both, cost and performance are uncertain parameters as long as no full-scale plants are realized. Grossmann (2009) estimates that the full costs of the first lignite pre-combustion CCS plant will exceed 2 billion Euros. We assume a capture rate for emission of 80% as expected rate given in Fishedick et al. (2008). Costs for on- and offshore wind projects are taken from Jeske (2009) including turbines, construction and grid connection. Efficiency levels for the standard technologies increase over time (Figure 7), and capital costs are assumed to remain steady. For CCS, additional variable costs include transport and storage of CO₂, which are assumed to be 7 €/tCO₂.

Investment into technologies in each period is constrained to prevent a single technology from becoming dominant within a few periods. The investment cap in combination with the decreasing plant availability implements an upper capacity level for each technology. Only wind reaches this level, since on- and offshore capacity is limited by locations which are provided with sufficient wind condition. A way to account for limited power plant production capacity is to

Table 2: Technology Data

Technology	Capital costs [€/MW]	Build-up time [yr]	Full load [h]	OM costs [€/MWh _{el}]	Lifetime [yr]
Lignite	1200	4	7500	3	40
Nuclear	2500	4	8000	3	40
CCGT	750	2	7000	2	30
Lignite CCS	2200	4	7000	6	40
Onshore wind	1500	1	1750	1	20
Offshore wind	3000	2	3500	1	20

use convex cost functions for the investment price depending on the installed capacity in each period. However, we do not have data to calibrate these functions. The values for the investment constraint are 2 GWa for lignite, nuclear, CCGT and lignite CCS plants. The constraint for on- and offshore wind is set to 1.5 GWa. Fuels are specified by their prices and a specific carbon emission factor, taken from Ipcc (2006). We included only moderately increasing prices for lignite and uranium of 1% annually, and 3% for natural gas. However, even slight variations in the price for lignite and uranium will affect windpower’s competitiveness (see 3.4.1).

Table 3: Fuel Data

Fuel	Price [€/MWh _{th}]	CO ₂ emission factor [CO ₂ /MWh _{th}]
Lignite	5	0.4
Uranium	5	0
NG	20	0.2

3 Scenario Analysis and Results

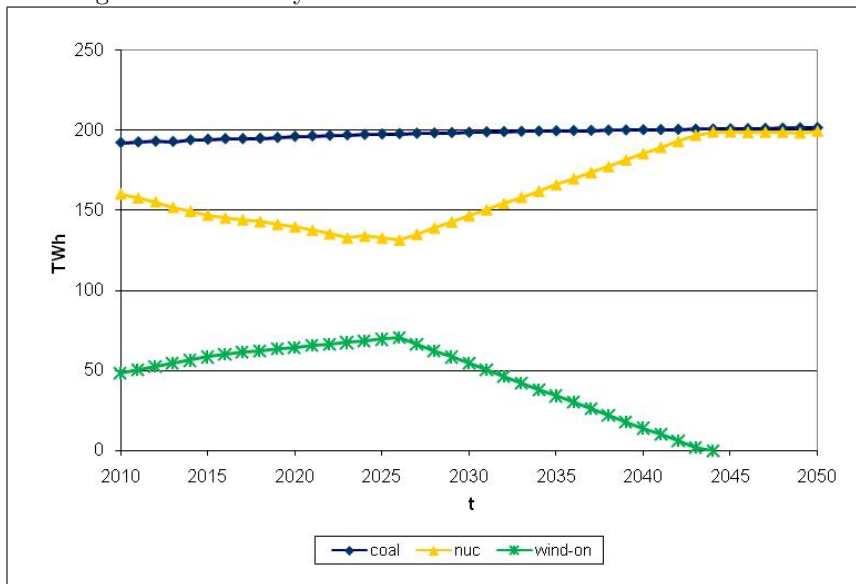
We first model a base case which is used to calibrate the model and to find reference values that act as benchmarks for additional analysis. Then we conduct a comparative scenario analysis including scenarios for emission reduction targets, the phase-out of nuclear generation, and learning.

3.1 Benchmark Scenario and Model Calibration

The initial power plant mix in the model is the German base-load capacity of 27 GW lignite, 22 GW nuclear and 22 GW onshore wind. The latter supplies only a small part of the demand due to the low full-load hours of onshore wind. Onshore wind electricity production is unsubsidized, and despite significant learning in the past, is still not competitive with other base-load technologies. We therefore model exogenous capacity investment under the German feed-in tariff, assuming that 35 GW are reached in 2025. From then on, subsidies are no longer paid and

investment becomes only endogenous. Emissions are constrained to the level of the initial power plant mix, 174 Mt_{CO_2} , and remain constant over time. The investment pattern in this scenario BS (Figure 1) describes the continuation of the status quo. With lignite being the cheapest base-load technology when no carbon prices are taken into account, scenario BS uses lignite up to the level on which the emission restriction is reached. The small increase in the share of lignite is based on the exogenous efficiency improvement allowing plants built in later periods to increase output but still emitting the same amount of CO_2 . The remaining demand is supplied by nuclear and onshore wind. Although nuclear electricity production appears rather uncompetitive in liberalized markets, scenario BS is different. Given the data on efficiency and capital costs and the high availability of the plants, nuclear generation costs are the second-lowest resulting in a stable nuclear share in the modeled time frame. Onshore wind, despite becoming cheaper, is used only as capacity is added exogenously, subsidized by the feed-in tariff. We note that for Germany, with less than 2,000 full-load hours annually, onshore wind will likely depend on subsidies for years.

Figure 1: Electricity Production in the Benchmark Scenario BS



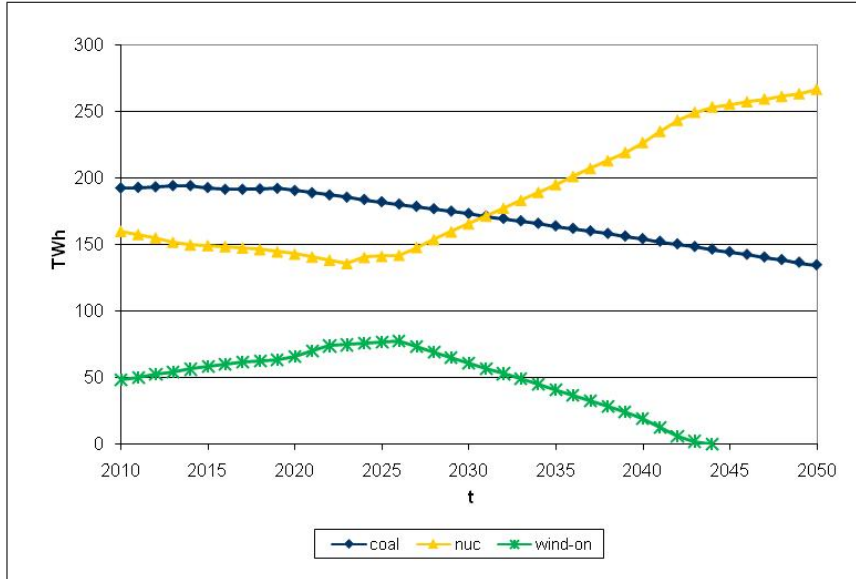
To sum up, absent a stringent climate policy, we cannot expect any change in the way electricity is produced, even though innovative technologies like offshore wind and CCS have the potential to replace some parts of the old system. As a result of missing incentives to pay for the learning investment, socially desirable technologies do not come to market.

3.2 Scenario 1 (S1): Emission Reduction

Scenario S1 assumes the implementation of a more serious climate policy resulting in a permit reduction of 1% per annum, starting in 2020 reaching 30% in 2050. One would expect that within this policy framework wind and CCS would be favored. However, the results show new investments in nuclear plants only

(Figure 2) when the permit reduction allows capacity replacement for both the depreciation of nuclear and lignite capacity due to the plants' longevity and high availability. Consequently, the prices for both electricity and carbon emission show no significant changes.

Figure 2: Electricity Production in Scenario S1 (Emission Reduction)



3.3 Scenario 2 (S2): Emission Reduction and No Nuclear

Scenario S1 shows that nuclear would be the preferred technology to reduce carbon emissions, but a stringent climate policy does not automatically result in an extension of CCS (or of renewable energy technologies) because nuclear electricity production is a barrier to their growth. However, the energy policies of some countries restrict specific generation. Austria for example has never commissioned a nuclear power plant. Germany will decommission its entire nuclear fleet within the next 12 years. Thus, scenario S2 includes nuclear phase-out. The results show that the occurring gap due to nuclear phase-out is largely filled by CCS supplemented by on- and some offshore wind (Figure 3 and Figure 4).

Figure 3: Generation capacity investments in Scenario S2 (No Nuclear and Emission Reduction)

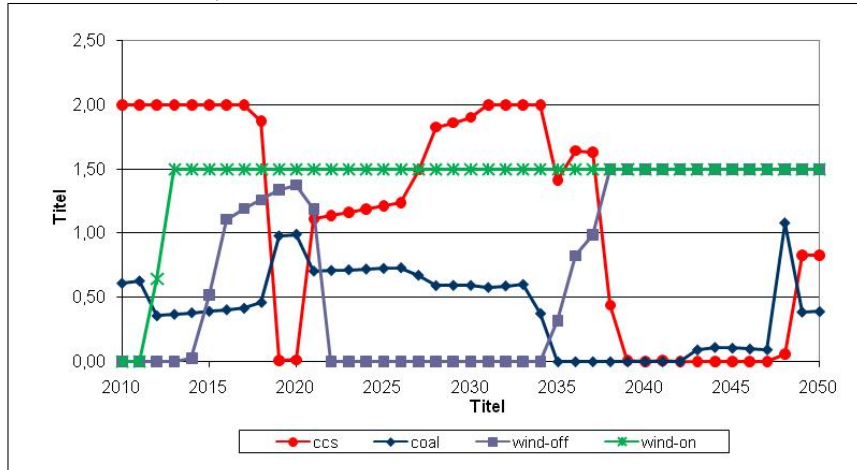
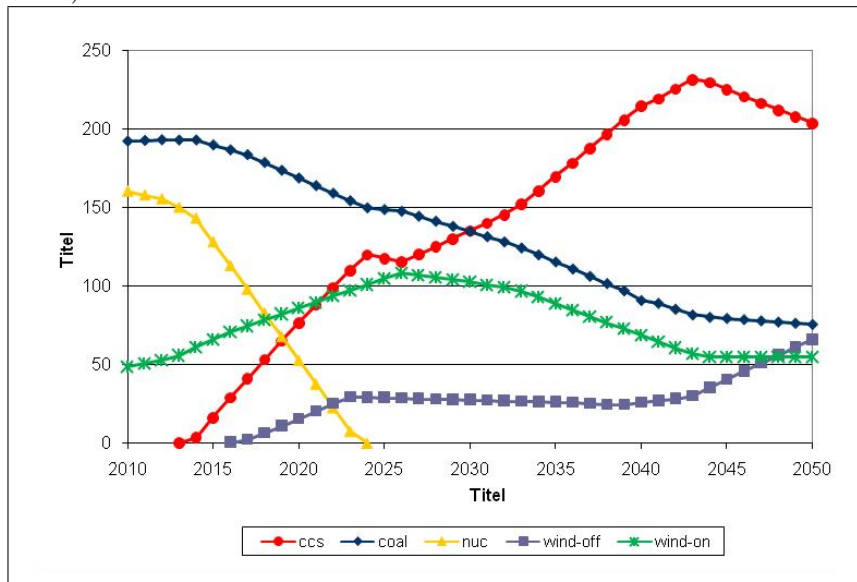


Figure 4: Electricity production in Scenario S2 (No Nuclear and Emission Reduction)



3.4 Scenario 3 (S3): Technological Learning

The results for scenarios BS, S1, and S2 do not account for the effect of LBD. As discussed in Section 1 and in Appendix A, learning is considered a crucial factor for fostering technological change. Hence, within scenarios S2 and S3, we apply an adjusted model with learning (Section 2.2) to the data sets assuming the learning parameter as shown in Table 4.

Table 4: Learning parameters

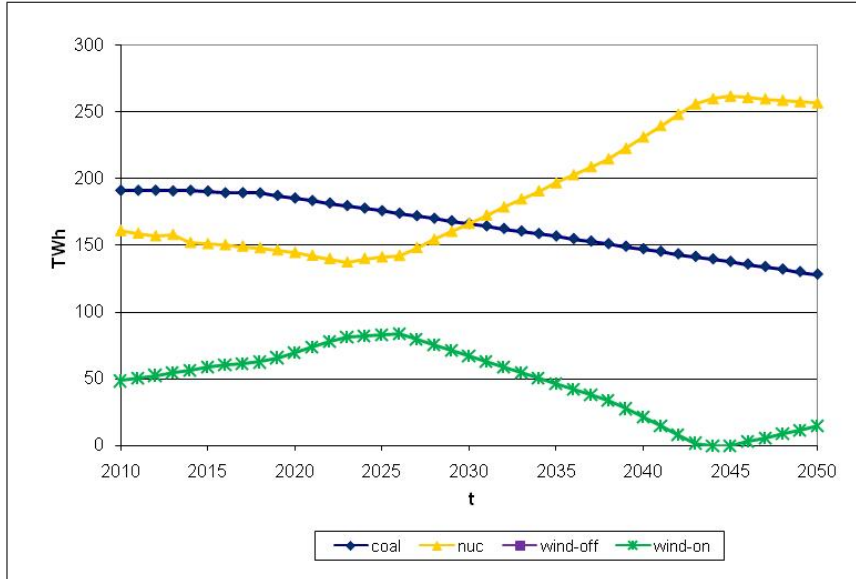
Technology	Elasticity η	$gen_{g,0}$ [TWh]	Elasticity CC	$cap_{g,0}$
CCS	0.025	10	0.1	4
Wind onshore	0	0	0.18	20
Wind offshore	0	0	0.18	4

Source: Rubin et al. (2006), McDonald and Schrattenholzer (2001).

3.4.1 Scenario S3a (S3a): Emission Reduction

In this scenario, emission restriction combines with endogenous learning. Results in the first periods do not differ significantly compared to scenario S1. Onshore wind capacity now no longer remains dependent on subsidies beyond the year 2040, since generation costs can be reduced such that wind can compete with base-load technologies (Figure 5). For offshore wind, technological learning leads to its application after 2035 but only if the prices for lignite and uranium increase by 2% annually (Figure 9). In the case of constant fuel prices, we observe no endogenous investment in wind, which is phased out after subsidized capacity installation end (Figure 10).

Figure 5: Electricity production in Scenario S3a (Emission Reduction)



3.4.2 Scenario S3b (S3b): Emission Reduction and No Nuclear

Considering the generation investments under scenario S3b the maximum expansion limit is used for offshore wind for the entire period (Figure 6). CCS capacities, however, experiences two strong periods of investment. The first (between 2010 and 2020) supports nuclear-phase out together with onshore wind while offshore wind production is built up. The second (starting in 2030) absorbs the decrease in coal production (Figure 7) because offshore wind reaches its technical maximum.

Figure 6: Generation capacity investments in Scenario S3b (LBD and No Nuclear and Emission Reduction)

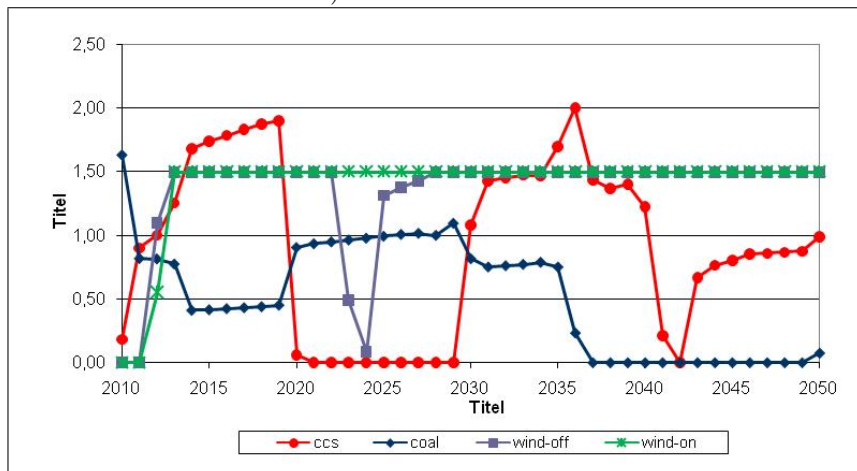


Figure 7: Electricity production in Scenario S3b (LBD and No Nuclear and Emission Reduction)

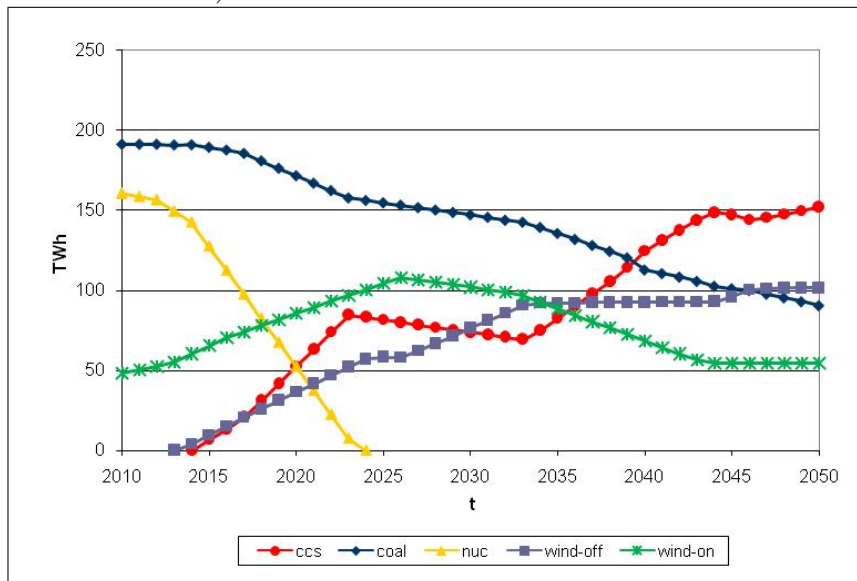


Table 5: Average electricity and emission prices

	BS	S1	S2	S3a	S3b
Electricity price [€/MWh]	59	61	83	60	68
Carbon price [€/tCO ₂]	5	5.5	8	4.5	5

We note that in this scenario CCS can act as a bridge technology for offshore wind. However, offshore wind cannot entirely replace production since a large portion of CCS must cover demand when wind is at its maximum. Without another large-scale renewable technology, CCS coexists as the most economic alternative to coal and nuclear but the consequences are higher electricity prices driven by higher carbon prices (Table 5) and the overall worse performance of CCS compared to the standard technologies. Our model does not confirm that natural gas will play an increasing role for base-load electricity production. Even in scenario S2 (nuclear is phased out but no endogenous learning is active), we do not observe investment in CCGT. This result is independent from increasing or stable fuel prices. However, natural gas will remain the only large-scale alternative to coal and nuclear apart from wind if CCS does not become an applicable technology.

4 Conclusion

This paper developed a dynamic model to analyze the diffusions process of the CCS technology under different assumptions. The model was applied to a data set based on the German electricity market. When there was no stringent carbon emission policy, CCS and wind were not implemented. We found that CO₂ reduction was mainly achieved by nuclear expansion. If such nuclear expansion was not possible, e.g., due to political restrictions, CCS became the economically preferred alternative even in the absence of learning effects. When learning effects were considered, offshore wind expanded strongly. However, CCS still has to support the process of reducing carbon emissions. The endogenous application of onshore wind under the German conditions is not alone achieved by learning or carbon reduction. Due to the low full load hours, competitiveness will depend on increasing the prices for conventional fuels. However, particularly in this case the society has to bear higher electricity prices.

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A Learning

As discussed in Section 1, the issue of learning is often treated as being closely related to technological change or technological innovation.

Learning effects, formally expressed as learning rate, progress ratio or experience curve, result in a reduction of unit costs or a better performance, as experience with a product or process is gained. Wright (1936) is the first to describe the concept of experience curves. He noticed that in airplane manufacturing, labor time requirements decreased by a constant percentage each time cumulative output doubled. In this paper, two types of learning are taken into account:

1. Learning-by-doing - which states that the unit costs decline with the number of units sold as a consequence of experience gained in production. Good examples for pollution-controlling technologies are flue gas desulfurization and catalytic NO_x reduction. The unit costs, although first increasing due to changes in the technology, declined on a rate of 11% and 12% (Rubin et al., 2006) when applied large-scale. The independent variable for power plant technology is cumulative installed capacity, expressed in kW .
2. Learning-by-using - which states that the costs of producing a single output unit decline with the number of units produced. As it takes time to adjust new technologies or components to a firm's specific process, efficiency of the first CCS plants is assumed to be lower compared to subsequent plants. The independent variable here is the cumulative amount of

electricity generated with the underlying technology, expressed in TWh. Another determinate could be plant availability, expressed in full-load hours.

The standard expression for modeling the learning effect is in the form of a single-factor experience curve given in equation (12) (Barreto, 2001).

$$UC_t(CC_t) = a * CC_t^{-b} \quad (12)$$

with

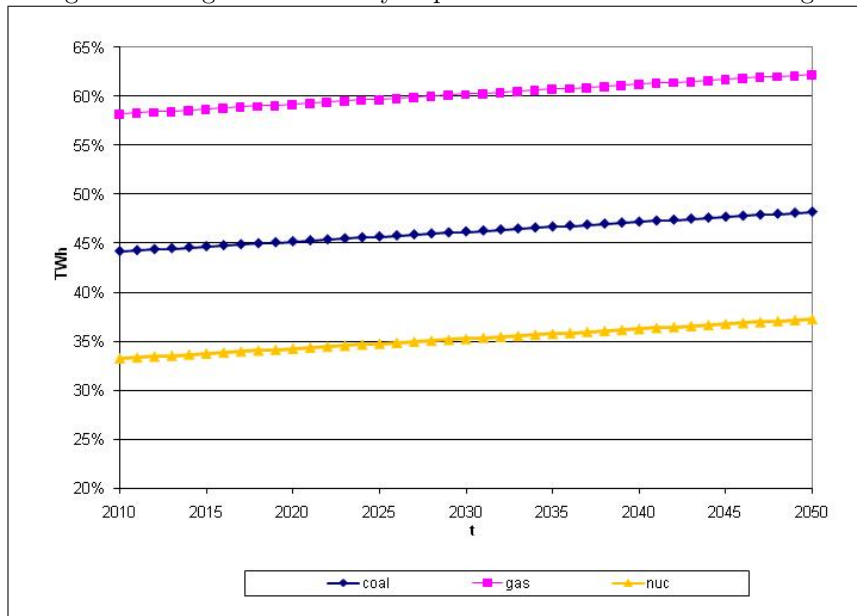
$$\begin{aligned} UC_t &= \text{Unit costs} \\ CC_t &= \text{Cumulative capacity} \\ b &= \text{Learning elasticity} \\ a &= \frac{UC_0}{CC_0^{-b}} \end{aligned}$$

A more common way to express technology's movement along the experience curve is by means of the progress ratio (equation 13). The progress ratio gives the rate at which costs (efficiency) improve if cumulative capacity (output) doubles. A progress ratio of 80% corresponds to a cost reduction or learning rate of 20% each time cumulative capacity doubles:

$$pr = 2^{-b} \quad (13)$$

B Exogenous Efficiency Improvement

Figure 8: Exogenous efficiency improvement of standard technologies



C Variation in Fuel Prices

Figure 9: Electricity production in Scenario S3a (Emission Reduction, High Fuel Prices)

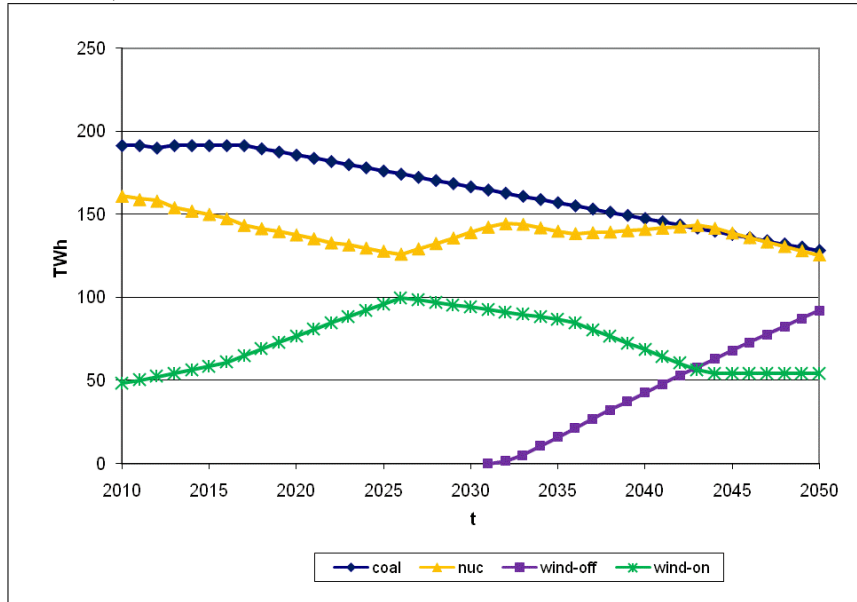


Figure 10: Electricity production in Scenario S3a (Emission Reduction, Constant Fuel Prices)

